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Behavior and asset markets: individual decisions, emotions and fundamental value trajectories

PROEFSCHRIFT

ter verkrijging van de graad van doctor aan Tilburg University op gezag van de rector magnificus, prof.dr. Ph. Eijlander, en Universitat Jaume I op gezag van de rector magnificus, prof. V. Climent Jordà, in het openbaar te verdedigen ten overstaan van een door het college voor promoties aangewezen commissie in de aula van Tilburg University op

vrijdag 19 december 2014 om 14.15 uur

door

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geboren op 2 oktober 1985 te Suceava, Roemenië

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Dr. Sigrid Suetens

“Live as if you were to die tomorrow. Learn as if you were to live forever.”

Mahatma Gandhi

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Contents

Summary

Since the early 1980s experimental methods have added new insights to complement the theoretical models intended to explain asset pricing and, in particular, stylized facts such as bubbles and crashes. Many of these factors are institutional, such as the ability to sell short or the specific market process used. Some others are directly related to market parameters such as cash and asset endowments or fundamental value time paths. However, the characteristics of individual traders are another factor that plays an important role in aggregate market behavior. In the first three chapters of this thesis we focus on some of these dimensions, and using experimental methodology and innovative software, we discover behavioral patterns that explain to some extent these phenomena. Other behavioral biases are analyzed in the fourth chapter regarding investment decision making in the framing of mutual funds.

The structure of the fundamental value time path of an asset is one variable that is demonstrated to determine the extent to which asset prices track fundamentals. In the first chapter of this thesis, we construct an asset market experiment in order to investigate how the time path of the fundamental value trajectory affects the level of adherence to fundamentals. In contrast to previous experiments with long-lived assets, in this experiment there is a phase in which fundamental values are constant before the onset of a trend, which is either increasing or decreasing, depending on the treatment. We compare the level of mispricing between the two treatments and we find that there is closer adherence to fundamental values when they follow a decreasing than when they have an increasing trend. Before the experiment begins, risk aversion, loss aversion, and cognitive reflection protocols were administered to traders. We find a number of patterns relating trader’s characteristics with market behavior. One is that greater average risk aversion on the part of traders in the market predicts lower market prices and the greater the level of loss aversion, the lower the quantity traded. A higher average on the cognitive reflection test score correlates with less deviation from the fundamentals. The variation between groups in risk aversion, loss aversion, and CRT score explains 45% of the variation in price level and in mispricing relative to fundamental between trader cohorts.

In the second chapter of this thesis we analyze the relationship between bubbles and crashes in an asset market and the emotions of traders. Previous work has shown that the

magnitude of bubbles is sensitive to environmental parameters such as the amount of liquidity available, institutional factors such as the ability to sell short and the trading institution, and the time path of fundamentals. Nonetheless, there is considerable variation within all conditions that is unexplained. That is, some sessions generate larger bubbles than others despite identical economic structure. We consider here whether variation in the emotional state of participants between different cohorts can account for some of this heterogeneity. To do so, we create an experimental asset market with the structure first studied by Smith, Suchanek and Williams (1988), which is known to generate price bubbles and crashes. Participants' facial expressions are analyzed with facereading software before and while the market is operating. The main finding is that greater positive emotion in facial expressions before the market opens predicts higher prices and larger bubbles. Greater fear predicts lower prices and smaller bubbles. Those traders who remain the most neutral during periods of market volatility achieve the highest earnings. Loss aversion in decision making is correlated with fear, but not with other emotions.

In light of the results obtained in the second chapter, we go one step further in the third chapter and analyze the dynamic relationship between emotions and market activity, at both the individual and market levels, in nearly real time. For this purpose we use a tick-by-tick dataset that matches individuals' trading activity with their emotional state throughout the market horizon. The individual analysis, in particular, allows us to gain a better understanding of the interaction between emotions, market variables and individual decision making. We document the feedback process, consisting of the effect of individuals' emotions on their behavior, the resulting impact on market-level variables and individuals' wealth, and in turn, the influence of market activity on the emotional state of traders. We find that positive emotional state enhances purchases and therefore overpricing. Also more emotions in general create more activity in a market, in particular more bids. These facts contribute to the creation of bubbles, which are sustained by approach emotions such as anger and happiness. As fear appears in the market, a crash becomes more likely to occur.

The last chapter of the thesis is focused on behavioral biases in mutual fund investment. There is an important branch of experimental literature that analyzes investor behavior, and in most cases unpredicted behavior appears, to a great extent related to the information available to the investors or to the framing of that information. These articles show that individual investors at times make suboptimal asset allocation decisions. We present a study that proposes a simple experimental design, which allows for an analysis of individual investor behavior in structured mutual funds according to variables such as expected return and risk (we vary the former while keeping the latter constant). At the same time, the protocol tries to eliminate possible behavioral biases such as the effect of past performance, of the disclosure of the probability distribution of the potential gains/losses, and of other features that might complicate comparisons: fees, non-portfolio services, etc. This approach also allows us to evaluate the effect that the structure of the available information has on investor behavior and, consequently, on the demand for the funds. The results show that when the investment alternatives are made easier to compare by showing the funds in increasing order of expected return, an anomaly we call the “too good to be true” effect disappears.

Chapter1.

Fundamental value trajectories and trader characteristics in an asset market experiment

1. Introduction

The tendency for experimental markets for long-lived assets to price at levels that differ from intrinsic values is one of the most robust and puzzling results from research in experimental markets. This result, first established by Smith et al. (1988), has been replicated in numerous studies, though the extent and pattern of mispricing is affected by a number of factors. These include the levels of endowment of shares and cash available for transactions (Caginalp et al., 1998; 2000), the trading institutions employed (Lugovskyy et al., 2012), the training of subjects (Lei and Vesely, 2009), and the induction of emotions (Andrade et al, 2012; Lahav and Meer, 2010). See Palan (2013) for an overview of this research.

One factor that has long been suspected as a source of mispricing in the Smith et al. (1988) experiment is the declining time path of the fundamental value. Because the asset is finitely-lived, and pays a dividend in each period, the intrinsic value, which equals the expected sum of future dividends, declines after each dividend has been paid. Some authors have claimed that this declining fundamental value structure is unfamiliar to experimental subjects, who are typically used to appreciating assets outside the laboratory (Noussair et al., 2001; Kirchler et al., 2012). The claim is that the declining fundamental value serves as a source of confusion for subjects. Indeed, it does appear that subject misunderstanding plays a role in generating mispricing in such an environment (Lei et al., 2001; Lei and Vesely, 2009; Kirchler et al., 2012; Cheung et al., 2013).

There is evidence that the time path of fundamentals can affect the extent to which prices track fundamentals. Noussair et al. (2001) compare markets in which the fundamental value is constant over time to ones in which it is decreasing. They find that the setting with constant fundamentals generates less mispricing. Giusti et al. (2012) compare settings in which fundamentals are increasing versus decreasing. In their setting, the cash held by traders earns interest, and with a sufficiently high interest rate, the fundamental value of the asset increases over time. They observe a strong pattern; fundamental value trajectories with an increasing trend are more conducive to pricing close to fundamentals than those that are decreasing. Huber al., (2012) implement decreasing fundamental value trajectories with dividend payments, and increasing time paths by imposing taxes (in effect negative dividends), on those who hold units at the end of each period. They observe that a decreasing trend leads to overpricing and an increasing trend to underpricing, though the increasing trajectory departs to a lesser extent from fundamental pricing. Both treatments exhibit a rapid adjustment of prices in the direction of the fundamental near the end of the life of the asset.

The most closely related study to the one reported here is that of Noussair and Powell (2010). They study two treatments, called Peak and Valley. The treatments differ from each other in only one aspect. In Peak, the fundamental value of the asset increases for first eight periods of the 15-period horizon, and then declines for the remaining seven. Under Valley, the value declines for the first eight periods and then increases for seven. There is a strong difference in the speed and extent of price discovery between the two treatments. Prices adhere to fundamentals much more closely in the Peak than in the Valley treatment. When the early and late periods of the asset's time horizon are considered separately, the decreasing trajectory exhibits better price discovery when it follows a phase of increase than when it precedes it. In contrast, prices under the increasing trajectory track fundamentals more closely when it constitutes the first phase of the time path rather than the second.[1]

The above discussion suggests that the timing of the onset of a fundamental trend and the time path of intrinsic value preceding the beginning of the trend might be a crucial factor influencing price discovery. A phase of trading before the onset of a trend allows a redistribution of units and cash among traders, as well as the accumulation of experience. Thus, the trend in fundamentals begins under different conditions than it would if were to set in immediately. In this chapter, we report the results of a new experiment that is designed to consider the relationship between the time path of fundamental value and the price discovery process under such conditions. The experiment has two treatments. In the *Bullmarket* treatment, the time path is constant for the first half of the life of the asset, after which there is an increasing trend in fundamental value for the remainder of the life of the asset. In the *Bearmarket* treatment, the phase of constant fundamentals is instead followed by a decreasing trend in the second half of the asset's life. We find that the Bearmarket treatment exhibits

[1] It is important to note that in all of the previous experimental studies mentioned in this introduction, subjects know what the fundamental value of the asset would be at each time period in the future. Thus, fundamental value trends are always accurately anticipated in advance. In the study we conduct here, we continue with this practice.

closer adherence to fundamental value than the Bullmarket treatment. Thus, the addition of the initial phase with constant fundamentals before the onset of the trend induces a reversal of the results of Giusti et al (2012) and Huber et al. (2012), who observe that price discovery is better for increasing trends.

In our experiment, before subjects participate in the asset market, they complete three individual choice tasks. These are described in detail in section 2.2. First, participants' loss aversion is measured with a version of the protocol used in Fehr and Goette (2007). Second, the willingness/ability to reflect about their decisions is elicited with a cognitive reflection test (CRT) as described in Frederick (2005). Third, risk aversion is measured with the procedure of Holt and Laury (2002). The data from these tasks permit us to consider the link between risk aversion, loss aversion, and cognitive ability on one hand, and market behavior and individual trading strategies on the other.

As described in section two, we advance a number of hypotheses about the relationship between loss aversion, risk aversion, cognitive reflection, and market behavior. In particular, we hypothesize that the average risk aversion of participants in a market is correlated with the average price level, with more risk aversion associated with lower prices. We also hypothesize that the average level of loss aversion of market participants is predictive of the quantity traded, with more loss aversion correlating with lower transaction volume. The last hypothesis is that greater average CRT score among the trader cohort predicts lower mispricing relative to fundamental value. As described in section four, all three of these hypotheses are supported, at least to some extent. Furthermore, we observe correlations between the responses on these measurement protocols and trading strategies. Risk-averse agents are less likely to trade based on market momentum, and loss-averse agents are less likely to speculate. Those scoring more highly on the cognitive reflection test are more likely to behave as fundamental value traders. Thus, intuitive relationships exist between measures of individual characteristics and trader behavior in the asset market.

2. The Experiment

2.1. General structure

The experiment consisted of sixteen experimental sessions. Twelve of these sessions were conducted at the CentER laboratory at Tilburg University, the Netherlands. The other four took place at the Laboratorio de Economía Experimental (LEE) facility at the University of Jaume I, Castellon, Spain. The sessions at Tilburg were conducted in English and those in Castellon were in Spanish. The English version of the instructions can be found in the Appendix. All participants were students enrolled at one of the two universities. Between 7 and 9 individuals participated in each session. Each session consisted of four parts and took on average approximately two hours. Average earnings were 22.64 Euro.

2.2. Risk Aversion, Loss Aversion, and Cognitive Reflection Measures

Each session consisted of four parts. The first part was the administration of a protocol to measure loss aversion. We employed a version of the elicitation procedure used by Fehr and Goette (2007), which is a series of six choices, presented in a price list format. Subjects completed the task using a pen and paper. The choices were presented on one sheet of paper. This meant that subjects could revise their earlier decisions in light of their choices in subsequent ones.

Each task required the person to indicate whether she would like to play a gamble which yielded a gain of 4.5 Euro with probability .5 or a loss of an amount x with probability .5. Depending on the decision task, x took on values of {.5, 1.5, 2.5, 3.5, 4.5, and 5.5 Euros}. Each value of x appeared in exactly one decision task that each subject completed. Subjects submitted all of their choices simultaneously when they turned in their sheet of paper to the experimenter. Only one of the decisions counted toward their earnings. The decision task this would be was determined after all decisions were turned in. A die was rolled, determining which decision would count for each participant. If a subject had chosen not to play the relevant gamble, she received a payoff of zero for part I of the experiment. If a participant chose to accept the selected gamble, a coin was flipped to determine whether she received 4.5 Euro or the negative payment specified in the gamble. A separate coin was flipped for each participant who chose the gamble. We used the number of gambles one was not willing to accept as a measure of her loss aversion.

Parts two, three, and four of the experiment were computerized. In the second part of the experiment all subjects completed the cognitive reflection test developed by Frederick (2005). Subjects were given three minutes to answer three questions, and they received 1 Euro for each correct answer. The three questions were:

1. A bat and a ball cost a total of 1.10 Euro. The bat costs 1 Euro more than the ball. How much does the ball cost?
2. If it takes five people five minutes to make five widgets, how long does it take 100 people to make 100 widgets?
3. In the lake there is a patch of lily pads, which doubles in size every day. It takes 48 days for the patch to cover the entire lake. How many days does it take the patch to cover half of the lake?

This test has been used extensively in experimental economics to measure the ability (or willingness, depending on the researcher's interpretation of the test) to reflect in answering a question. Akiyama et al (2013), when investigating the mispricing in an experimental asset market, find that the effect of strategic uncertainty on trading decisions is greater for subjects with a perfect score in the Cognitive Reflection Test, and it is not significant for those with low scores. Corgnet et al. (2013) find that subjects with lower CRT scores tend to trade at prices that can result in losses.

The questions have the feature that the first answer that typically springs to mind is an incorrect one, but that the correct answer is simple upon some reflection. We took the number of correct answers as a measure of how prepared an individual is to reflect about a decision situation.

In part three, subjects' risk aversion levels were measured using the Holt-Laury (2002) protocol. Under this procedure, subjects make a series of 10 choices between a relatively low-variance, and a relatively high-variance, lottery. The choices follow a price list format, in which the high-variance lottery takes on an ever greater expected value relative to the low-variance lottery. The probability at which the individual becomes willing to accept the riskier lottery implies a level of risk aversion. Specifically, there is a series of ten choices between two lotteries of the form (p, x_1; 1-p, x_2) and (p, y_1; 1–p, y_2) where $y_2 > x_2 > x_1 > y_1$, and p varies monotonically from .1 to 1 in increments of .1 in the ten different choices. In our experiment, we set $y_2 = 3.85$, $x_2 = 2.00$, $x_1 = 1.60$, and $y_1 = 0.10$, denominated in Euro. Thus, a person choosing the relatively low-variance lottery (p, x_1; 1-p, x_2) for $p \leq .4$, and the high-variance lottery (p, y_1; 1–p, y_2) for $p > .4$, was consistent with risk neutrality, the maximization of expected value. Fewer (more) than four safe choices are consistent with risk-seeking (risk-averse) preferences. The ten decisions were presented on one screen, so that individuals could revisit and revise their responses to previous questions in light of latter ones. When they were satisfied that they did not want to change any of their responses, they submitted all ten of them simultaneously.[2] One of the 10 questions was randomly selected to count toward earnings.

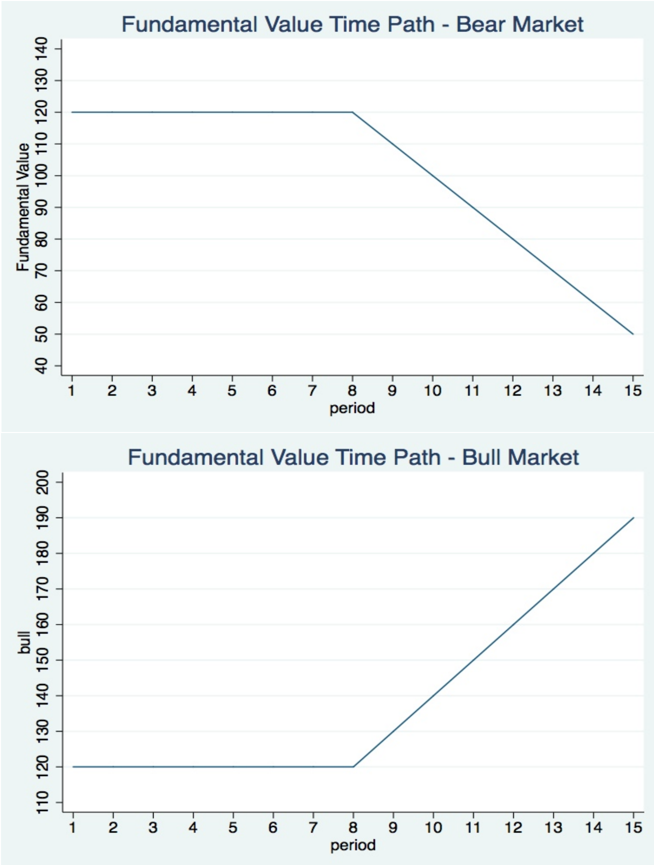
2.3 The Market and the Two Treatments

The fourth phase of the experiment was the most lengthy and consisted of a sequence of two asset markets, both identical in parametric structure. Each market consisted of 15 periods, during which individuals could trade units of an asset. The asset's lifetime equaled the 15 periods during which the market was in operation. An experimental currency called ECU, converted to Euros at the end of the experiment, was used for all payments, transactions, taxes and dividend distributions. After the first 15- period market had elapsed, a second market was conducted. The second market was reinitialized to conditions identical to those prevailing at the beginning of the first market. Thus the first and second markets began under identical conditions except for the level of experience of traders.

There were two treatments, called *BearMarket* and *BullMarket*. The *BearMarket* treatment was characterized by a time path of fundamentals that was constant during the early portion of each market and decreasing during the latter portion. The decreasing trend began in period 8 of each market. The *BullMarket* treatment consisted of markets in which the fundamental value was constant in the early periods of the market, and increasing beginning in period 8. The time path of fundamentals in the two treatments is illustrated in Figures 1a and 1b. In the figures, the horizontal axis indicates the period number. The vertical axis indicates the fundamental value, in terms of ECU, the experimental currency. Subjects knew at all times what the fundamental value would be in all future periods, and thus the change in the trend of fundamentals was anticipated.

[2] Only 5% of the participants made inconsistent choices, that is to say, they chose the safe lottery, then switched to the risky lottery, and finally chose the safe option again in the choice list. For these subjects the risk aversion measurement was the number of safe choices they made in total, regardless the switching point.

Figure 1: Fundamental Value Time Paths, Both Treatments



The fundamental value of the asset arose from three sources: dividends, taxes/subsidies, and a final buyout. This final buyout was a payment for each unit of asset held at the end of the market, that is, at the end of period 15, to the unit's owner. All three components of fundamental value were in effect payments to or by the current owners of the asset on each unit they held. Because the asset is finitely lived, at any point in time the fundamental value was the sum of the expected net future financial flows from all three sources. Specifically, the fundamental value of a unit of the asset during any period was equal to the sum of the expected dividends and final buyout it would generate, minus any taxes and plus any subsidies that remained to be paid on the unit. Thus, the fundamental value of one unit of the asset at any point in time was the expected value of the stream of payments that resulted from holding the unit for the remainder of the current market. The three different sources of value were included in the design merely to induce the appropriate dynamic patterns in fundamental values. All three components were present in both treatments so that both conditions had the same level of complexity. The number and timing of future dividend draws, tax payments, and final buyouts in the current market was always common knowledge.

After every period, each unit of the asset paid a dividend to its current owner. Dividends were drawn independently for each period from a two-point distribution with equal probability of +10 or -10. In the experiment, the dividends were determined with a public coin flip. The result of the coin flip was then entered into the computer by the experimenter. The expected dividend in any period, and thus the expected future dividend stream, was equal to 0 ECU.

In periods 8 – 15 of each market in the BullMarket treatment, taxes were paid. After each of these periods, all subjects paid a fixed inventory tax of 10 ECU for each unit in their possession. The effect of these taxes was to create an increasing fundamental value trend during the periods that the tax was in effect. Each tax payment reduced the future tax liability on each unit by 10 ECU, and thereby increased the fundamental value by the corresponding amount.

In the BearMarket treatment, in periods 8 – 15 of each market, a subsidy of 10 ECU was paid in each period to the holder of any unit of asset. This had the effect of reducing the fundamental value in each of the last eight periods of the life of the asset. As each subsidy was received, the future flow of subsidy payments decreased by 10 ECU.

The third component of the fundamental value was the final buyout. This was a payment to the holder of each unit of asset at the end of the 15-period life of the asset. This payment was equal to 200 ECU in the BullMarket treatment and to 40 ECU in the BearMarket treatment. The values were chosen to make the fundamental value equal to an identical value of 120 over the first seven periods in both treatments. The final buyout ensured that the fundamental value of the asset was always positive.

Dividends, subsidies and final buyout payments were added to individuals' cash balances at the time they were paid out, and taxes were subtracted from cash balances at the moment they were incurred. This meant that positive dividend payments and subsidies added to the cash could be used for subsequent purchases. Negative dividends and taxes reduced the cash available for later purchases.

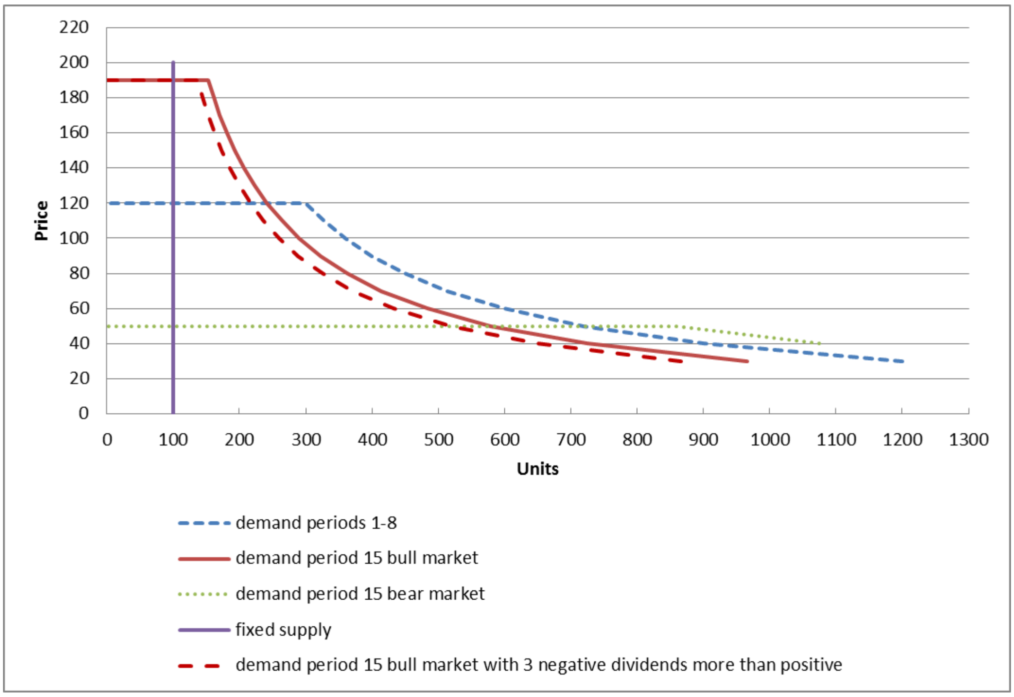
At the beginning of period 1 in each market, agents received an initial endowment of 10 units of asset and 3600 ECU of cash that they could use for transactions. Cash balances and asset inventories were required to be positive. In other words, margin buying and short-selling were not allowed. The markets were computerized and used continuous double auction trading rules (Smith, 1962) implemented with the z-Tree computer program (Fischbacher, 2007).

In a continuous double auction, the market is open for a fixed interval of time. At any time, any agent, who has sufficient cash or units to conclude the transaction, may submit an offer to the market. An offer specifies a price at which the agent is willing to either buy or sell a share. Any trader with sufficient funds and units of asset to complete the transaction may accept any outstanding offer at any point in time. All offers are displayed to all agents on their computer screens. Upon acceptance of an offer, a trade is concluded and the asset and cash transferred between the transacting parties. Within our 15-period markets, inventories of assets and cash carried over from one period to the next so that for each individual, the quantities of cash and assets held at the beginning of period t+1 were the same as those held at the end of period t, adjusting for any dividends and subsidies received as well as for any taxes paid. Each of the 15 periods of a market lasted two minutes.

A subject's entire earnings over a market were equal to the amount of cash he held at the end of the final period of that market, after the last dividend, tax/ subsidy, and final buyout were paid. This was equal to his initial endowment of cash, plus any earnings from dividends, plus any subsidies received, minus any taxes paid, plus proceeds from sales of shares, minus expenditures on purchases of shares, plus any final buyout received. ECU were converted to Euros at a rate of 500 ECU = 1 Euro.

Given the total initial endowment of cash and assets, we determine the demand and supply functions for the periods in which the fundamental value of the asset is constant. Also, considering the changes in the fundamental value and the cash constraints, we determine the demand functions for the last period of the two treatments in order to provide some insight about how the opportunity sets of traders at a given point in time affect prices. Figure 2 below shows a fixed supply of 100 units in a market with 10 traders. In such a market, the demand in any of the first eight periods of either of the two treatments, as shown in the graph, is determined by the total amount of cash available and the fundamental value of the asset that remains constant in these periods. Given the shape of the demand curve, transaction prices will tend to be lower than equilibrium prices (also this is the case of the last period of the bull market and bear market also shown in the figure) since it is the only way of realizing gains from trade for both buyers and sellers. In the last period of the bear market, the demand curve reflects the greater amount of cash available in the market relative to the value of the assets, due to subsidies received and the low fundamental value. These circumstances create a flat shaped demand up to a very large quantity. On the other hand, due to the cash constraints in the last period of the bull market, where the cash available for purchases relative to the value of shares is reduced because of taxes on each unit and a greater fundamental value, the point where the willingness to pay begins to decrease occurs at a lower quantity of units. In this case, if we consider the possibility of more negative dividends drawn in a session (as it can be seen in the example described by the dashed line in figure 2), the demand could be shifted in such a way that equilibrium prices would be below the fundamental value.

Figure 2: Demand and Supply Functions



3. Hypotheses

The five hypotheses we advance concern market-level activity, and are based on previous studies in experimental and behavioral economics. We readily concede that we anticipated some of the hypotheses to be more likely to be upheld in the data than others. Nevertheless, the hypotheses express what might reasonably be predicted from previous studies. The first is that the two treatments, BullMarket and BearMarket, would exhibit equally effective price discovery. Although Giusti et al. (2012) and Huber et al., (2012) find that increasing fundamental value trajectories exhibit better price discovery than decreasing ones, both of these studies differ from ours in a number of ways. The most basic difference is, of course, that our design features a delayed onset of the fundamental value trend. Thus, we maintain the ex-ante expectation that there would be no difference in adherence to fundamentals between the two treatments.

Hypothesis 1: The Bullmarket and Bearmarket treatments track fundamentals equally closely.

To evaluate hypothesis 1, we compare the *Average Dispersion* (*AD*) between the two treatments. This is an overall measure of market mispricing relative to fundamentals over the entire lifetime of the asset. It is defined as $AD = \Sigma_t |(p_t - f_t)|/15$, where p_t is the average price in period t and f_t is the fundamental value in period t. *AD* is the absolute difference between price and fundamental, averaged over the 15 period horizon. Hypothesis 1 is that *AD* is not different between the increasing and the decreasing treatments.

The second hypothesis also originates from previous experimental studies. These have shown that as the same subjects participate in a second market under identical conditions, the prices at which they trade move closer to fundamentals (Smith et al., 1988; Dufwenberg et al., 2005; Haruvy et al., 2007). Nevertheless, it is possible that the convergence to fundamentals would occur at different rates in the two treatments. This is suggested by the results of Noussair and Powell (2010), who find that experience leads to more rapid price discovery in their Peak than in their Valley treatment. This would suggest that convergence would occur faster in the BearMarket than in the BullMarket treatment. This is because the Bullmarket treatment has an upward fundamental trend in the latter part of the session, like the Valley treatment. In contrast, Bearmarket has a downward trend like the Peak treatment. However, our view is that the analogy is too speculative to advance an ex-ante hypothesis that convergence would occur at different rates in the two treatments.

Hypothesis 2: Greater experience leads to closer adherence to fundamental values. Market 2 tracks fundamentals more closely than Market 1.

The next three hypotheses concern the relationships between each of tasks in phases 1 - 3 and market activity in market 4. They concern whether measurement of traders' characteristics, such as risk aversion, loss aversion, and tendency to reflect, can predict the activity in the market in which they participate. Hypothesis three relates to risk aversion. Because the asset traded in our markets is a risky lottery, it should be valued less by relatively risk-averse agents. Thus, we hypothesize that a greater average level of risk aversion among participants in the session, as measured in part three of the session, would correlate negatively with price level in part four.

Hypothesis 3: Greater risk aversion on the part of the average trader is correlated with lower prices in the asset market.

We quantify price level using a measure called *Average Bias* or *AB* (Haruvy and Noussair, 2006). This equals $AB = \Sigma_t (p_t - f_t)/15$ and is a measure of price level relative to fundamentals. We correlate it with the average level of safe choices in part three, using each session as the unit of observation. Furthermore, within each session, we expect that relatively risk-averse individuals would be net sellers of units to relatively risk tolerant ones, exploiting the gains from exchange that can ensue from such a transfer of risk. By the end of the market, relatively risk tolerant agents should hold more units of asset than more risk averse ones.

Just as we assert that risk aversion is related to the price level, we hypothesize that loss aversion is related to the quantity transacted. Consider a loss-averse agent who has purchased a unit and now wishes to sell a unit. This agent may be reluctant to sell a unit at a price lower than the last price at which he purchased. Alternatively, this reluctance could occur at another reference price, such as the average price paid in previous purchases, but a similar intuition would emerge. Similarly, consider a loss-averse agent deciding whether or not to purchase a unit. He may be reluctant to purchase the unit at a price greater than a reference price, which might be for example the one at which he concluded his last sale. This reluctance to trade may create friction which would lower transaction volume. On the basis of this intuition, we hypothesize that the average loss aversion of a cohort measured in part 1 of the session is negatively correlated with the average quantity transacted in the markets, in which the cohort participates in later in the session.

Hypothesis 4: Greater loss aversion is correlated with lower transaction volume in the asset market.

At the individual level, we would expect the relatively loss-averse individuals within a session to conclude fewer trades than their less loss-averse counterparts. The final hypothesis concerns the relationship between market activity and the cognitive reflection test administered in part two of the experiment. The CRT test measures the willingness to think about a decision problem, and it is plausible to conjecture that individuals who are prepared to do so are also more likely to thinking about the fundamental value of the asset when trading in the market. Thinking about the fundamental might encourage an individual to use it as a limit price. Indeed, Corgnet et al., (2012) report that subjects with higher CRT scores tend to make purchases at price below, and sales at prices above, fundamental values. It is likely that the greater the proportion of people who approach their trading decisions in this way, the greater the tendency is for prices to be close to fundamentals. We thus hypothesize that Average Dispersion would be negatively correlated with the average CRT score of the traders in the market.

Hypothesis 5: Greater average CRT score is correlated with closer adherence to fundamental values.

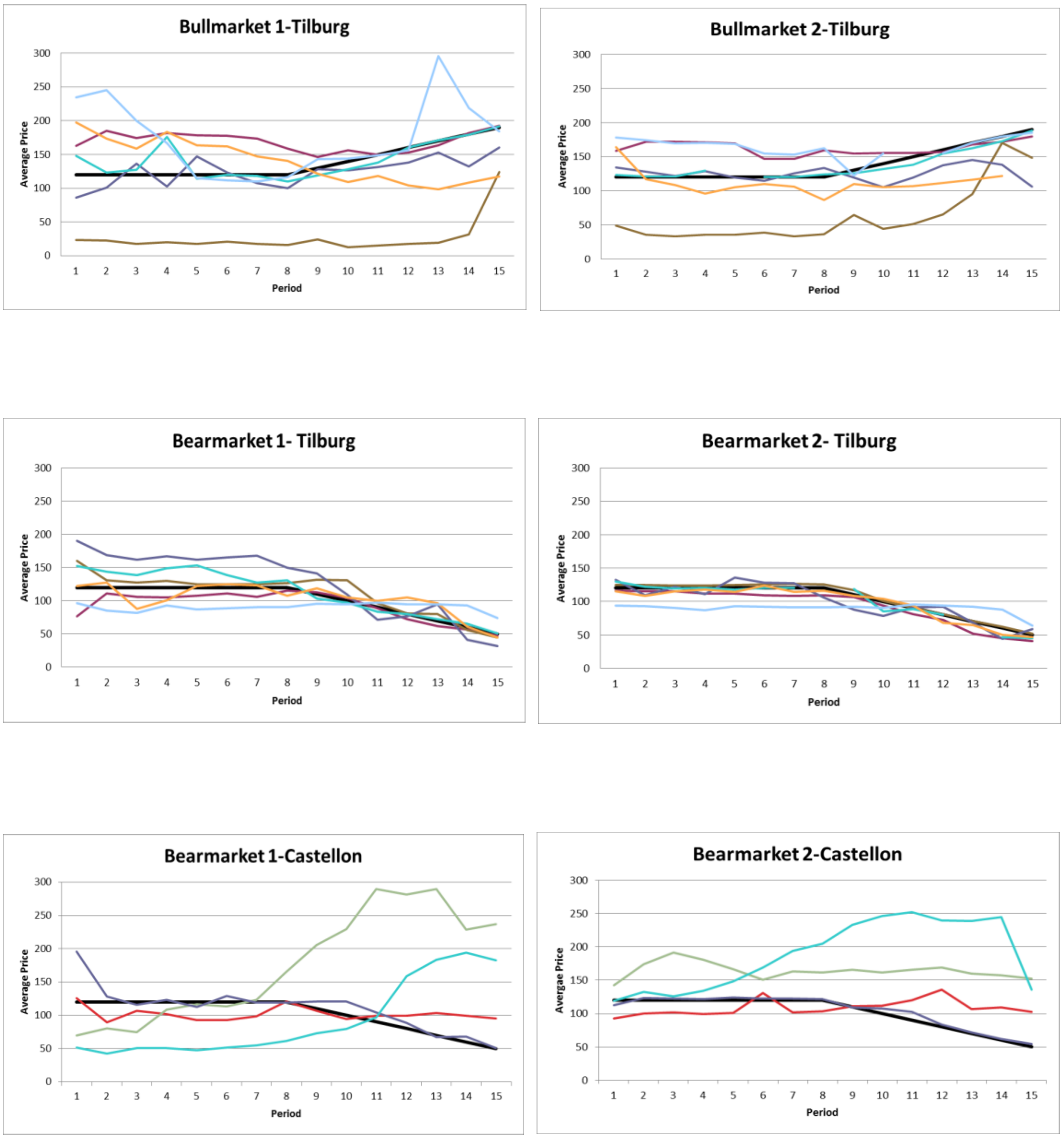
4. Results

4.1 Market Price Patterns and Treatment Differences

Figure 3 below shows the time series of transaction prices for each market in the two treatments. Each individual time series corresponds to the activity of one of the 16 groups. The two panels in the upper portion of the figure correspond to the first and second markets of the BullMarket treatment. The vertical axes indicate the price, the horizontal axes mark the time period, and the fundamental value is given by the bold black line. Each time series represents the average price in each period in one of the sessions. The middle portion of the figure represents the analogous data for the BearMarket treatment for the sessions conducted at Tilburg University. The lower portion contains the data from the BearMarket sessions run at Jaume I.

Figure 3 illustrates several basic patterns. The first is that prices in the BearMarket treatment are closer to fundamental values than those in the BullMarket treatment, especially for market 2 in the sessions conducted at Tilburg. The second is that prices in the second market within each treatment are closer to fundamentals than those in the first market in some sessions but not in others. In the BearMarket treatment sessions conducted at Tilburg, pricing in market 2 is obviously closer to fundamentals than market 1. The sessions conducted at Jaume I tend to exhibit greater deviations from fundamentals than those conducted at Tilburg. In the Bullmarket treatment, in the first eight periods, prices depart substantially from fundamental values, even in market 2.

Figure 3: Average Market Prices, All Markets



Left Panels: Market 1; Right Panels: Market 2

The data are the average transaction price in a period. Each time series is a separate session. The Fundamental Value Time Trajectory is given by the bold black line.

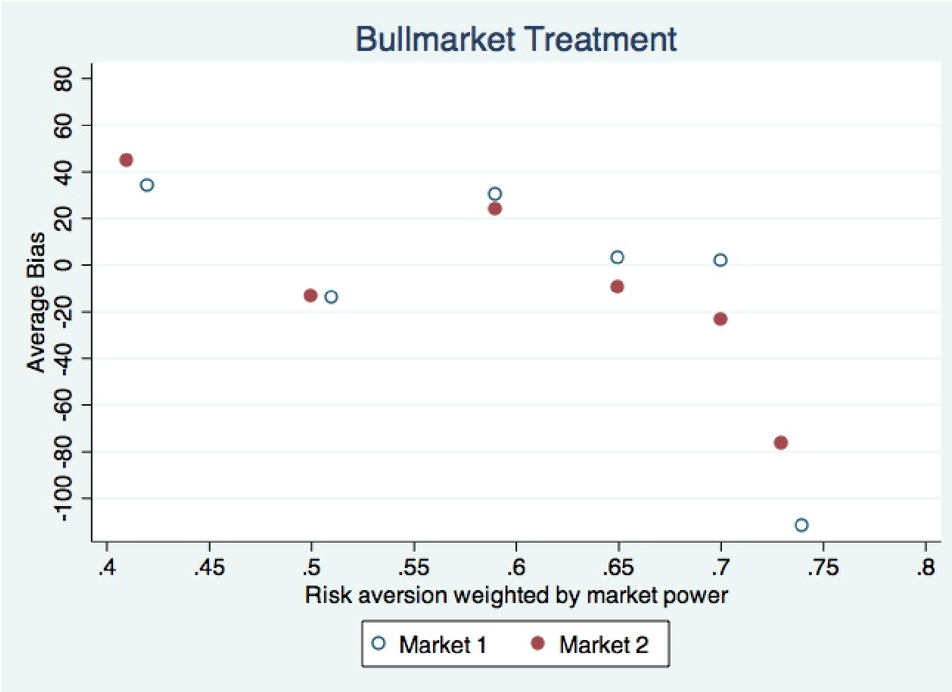
Statistical tests conducted using the 12 Tilburg sessions, enabling control for subject pool effects, confirm the impressions gleaned from the figures. A Mann-Whitney rank sum test fails to reject the hypothesis that the average dispersion is equal between the Bullmarket and Bearmarket treatments in market 1 (z = 1.441, p = .149). For market 2, however, the test yields z = 2.082 (p = .0379), which is significant at conventional levels. We thus support hypothesis 1, but only in market 2, when subjects have previously obtained experience with the market process. In market 2, the Bearmarket treatment leads to more accurate pricing.

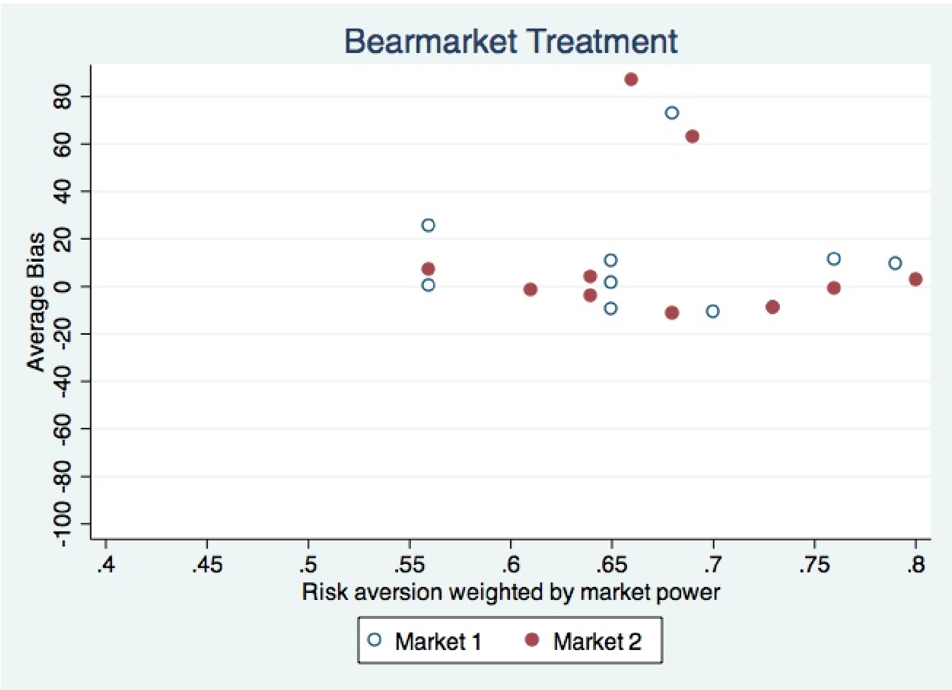
The average dispersion is lower in market 2 than in market 1 in only three of the six Bullmarket sessions. However, in all six sessions of Bearmarket conducted in Tilburg, prices exhibit lower average dispersion in market 2 than in market 1 (z = 2.082, p = 0.037) Thus, there is mixed support for hypothesis 2. It is supported in the Bearmarket treatment, but not in Bullmarket.

Figure 4 below shows the relationship between the average risk aversion of session participants and the price level measured by *AB* in each market. The risk aversion of each individual is weighted by her *market power* in the experiment, and this new variable constitutes the horizontal axis. The market power is a weighted average of the percentage of the shares outstanding and the percentage of the total stock of cash that an individual holds. It is used as a measure of influence in the market (see Haruvy and Noussair, 2006, or Haruvy et al., 2013). The market power of individual i at time t, denoted as MP_{it}, equals $.5*s_{it}/\Sigma_i s_{it}$ + $.5*m_{it}/\Sigma_i m_{it}$, The variable s_{it} equals the number of units of asset that i has at the beginning of period t and m_{it} is the amount of cash that individual i has at the beginning of the period. The weighting of risk aversion by market power is intended to reflect the fact that the risk attitudes of those individuals with greater capacity to buy and sell tend to have more influence on market activity.

In figure 4, The Average Bias for a market is indicated on the vertical axis. Each data point corresponds to one market in one session. The figure shows the relationship suggested in hypothesis three for the BullMarket treatment, though the relationship does not appear for BearMarket. For the pooled data from both treatments however, the correlation between average risk aversion for a trader cohort and the Average Bias in their market is -.528, significant at the p =.035 level in market 1. The correlation is -.511 in market two, significant at p = .042. Thus, we find strong support for hypothesis three in BullMarket and mixed support overall.

Figure 4: Correlation Between Risk Aversion Weighted by Market Power and Average Bias in each Market, Both Treatments

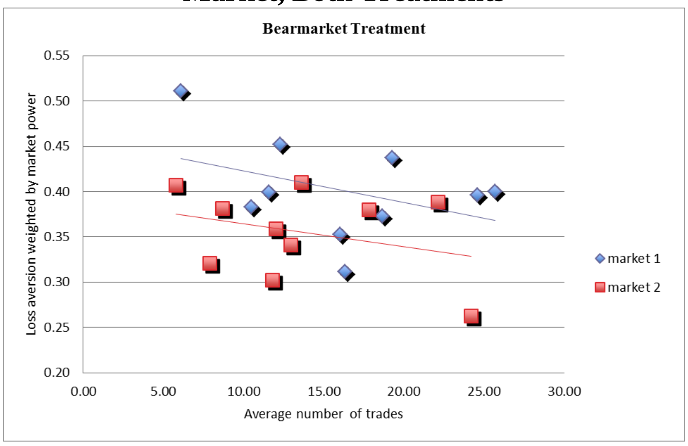


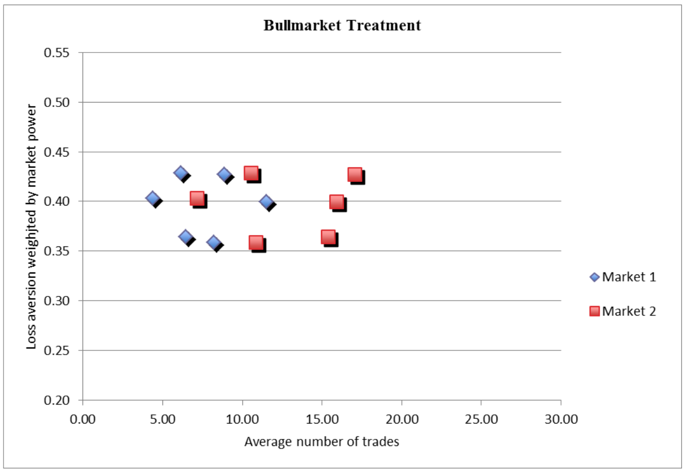


Risk aversion weighted by market power equals [(Number of safe choices in part 3 by individual i)*(i's average market power over the 15 period market)], averaged over all traders in the market.

Figure 5 illustrates the relationship between average trader loss aversion by session and the volume of trade in each treatment. The loss aversion of individuals in the session, weighted by their market power, is plotted against the volume of trade by session. The figure shows that there is a negative relationship (ρ -.19) in market 1 for the BearMarket treatment, which is consistent with hypothesis 4, though the correlation is not significant. The relationship is weaker in market two (ρ -.12), suggesting that the relationship becomes yet weaker with experience. There is no relationship between these two measures in the BullMarket treatment.[3] Overall, we find only very weak support for hypothesis 4.

Figure 5: Relationship Between Loss Aversion and Number of Transactions in a Market, Both Treatments



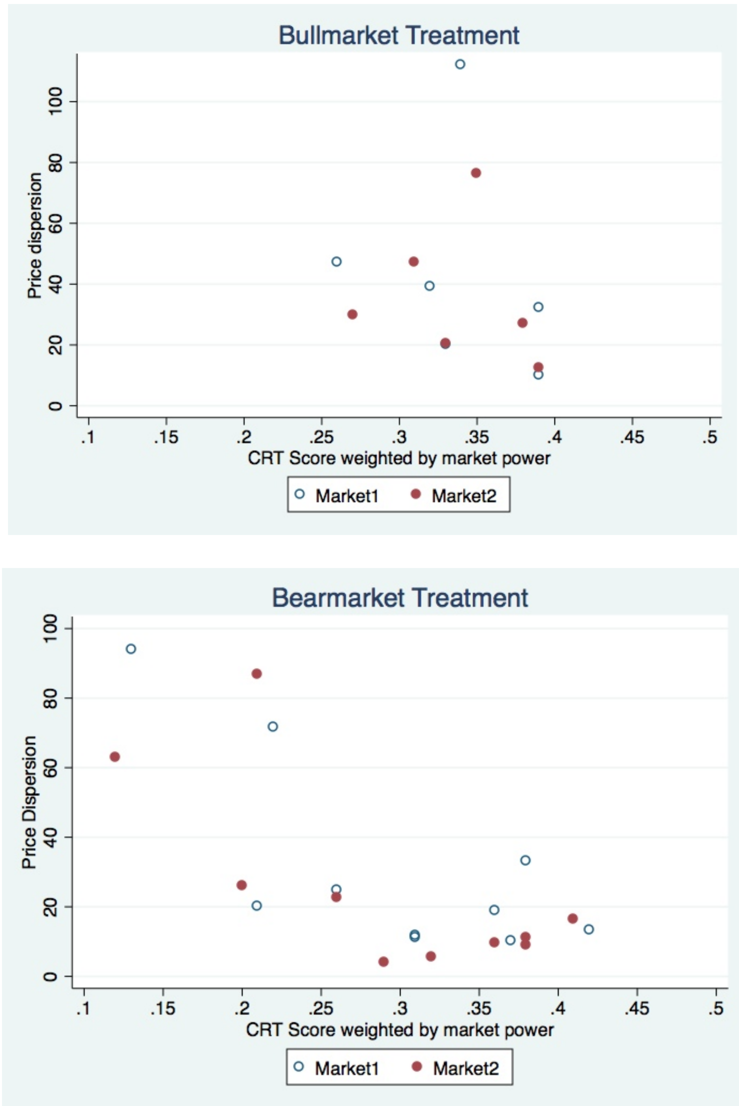


Loss aversion weighted by market power equals [(Number of safe choices in part 1by individual i)*(i's average market power over the 15 period market)], averaged over all traders in the market.

[3] Loss aversion might also influence prices when negative dividends are possible as is the case for the first 8 periods of either treatment when the fundamental value is constant and also for the last 7 periods in the BullMarket treatment. In this case, more loss averse traders might tend to sell more units when negative dividends are possible and this would lead to lower pricing than fundamentals. However, we do not find evidence of such behavior when correlating loss aversion with the number of units held by each trader at the end of period 8 (ρ= .006; p=.940). The correlation between loss aversion and number of units held at the end of period 15 in the BullMarket treatment was ρ= .105, also not significant (p=.451).

Figure 6 relates the average CRT score of session participants, weighted by their market power, to the Average Dispersion in each session. The figure shows that the greater the average CRT of the group, the closer is their conformity to fundamentals. The correlation is -.433 and significant in market 1, (p =.093) as well as market 2, -.442 (p = .086). Thus there is strong support for hypothesis 5. This result is enforced by a positive relationship between individuals' market power and their CRT score (ρ=.144; p=.094).[4]

Figure 6: Cognitive Reflection Test Score and Average Dispersion, All Markets.



[4] We also explored the possibility of a negative correlation of market power with loss aversion and risk aversion. We find no significant result for loss aversion (ρ= .02; p=.75 for Market 1 and ρ= -.02; p=.75 for Market 2). Risk aversion, on the other hand, seems to be negatively correlated with market power, though the relationship is only significant for the second market (ρ= -.09; p=.28 for Market 1 and ρ= -.17; p=.04 for Market 2)

4.1.1 Summary of market level results

This subsection has provided evidence that the BearMarket treatment adheres more closely to fundamentals than the BullMarket treatment. These results contrast with typical results obtained in markets for assets exhibiting an immediate onset of a trend in fundamental value, in which decreasing fundamentals are associated with greater mispricing. Also, under BearMarket, there is a systematic decrease in the level of mispricing in the second market that a cohort participates in compared to the first. The average risk aversion of traders correlates negatively with the price level. The average CRT score correlates negatively with the distance between price and fundamentals. In the next subsection, we explore the individual behavior underlying these patterns.

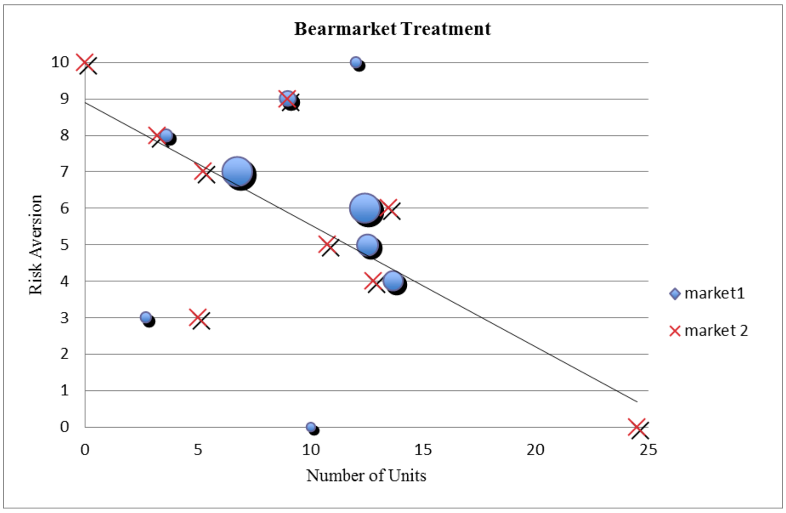
4.2. Individual Behavior

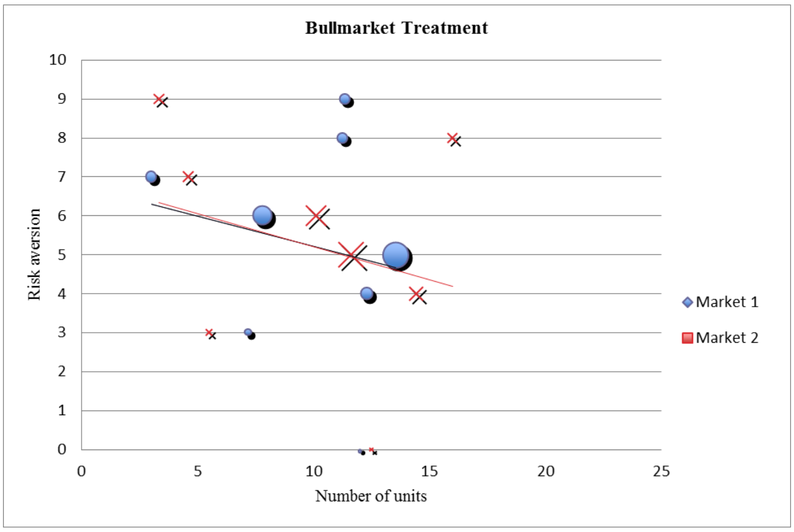
4.2.1. Risk aversion, loss aversion, CRT score, and individual trading behavior

We have observed, in section 4.1, that greater average risk aversion among market participants is negatively correlated with price level. We now consider whether relatively risk-averse individuals tend to sell to those who are less risk averse. This pattern would be reflected in a relationship between an individual's risk aversion, as measured in part 1 of the sessions, and how many units of the asset she holds at the end of the last period of the market. Figure 7 shows the relationship between an individual subject's risk aversion and her final asset holding at the end of markets 1 and 2. The vertical axis is the measured level of risk aversion in part 3 of the session, with 10 corresponding to the greatest, and 1 to the lowest, possible risk aversion level. Each data point in figure 7 is the average quantity held at the end of a session by individuals of a given risk aversion level. Larger circles indicate a larger number of individuals with the corresponding risk aversion level. The Appendix contains histograms of the risk aversion, loss aversion and cognitive reflection measures for out sample of participants.

The figure illustrates the tendency of individuals who are relatively risk averse to sell to those who are less risk averse. This intuitive relationship exploits potential gains from trade as risk is transferred to those who have a lower cost of bearing it. The correlation between the final inventory of an individual and her risk aversion in the BearMarket treatment is $\rho = -.197$, significant at $p = .073$. However, the correlation is insignificant under BullMarket ($\rho = -.035$, $p = .802$).

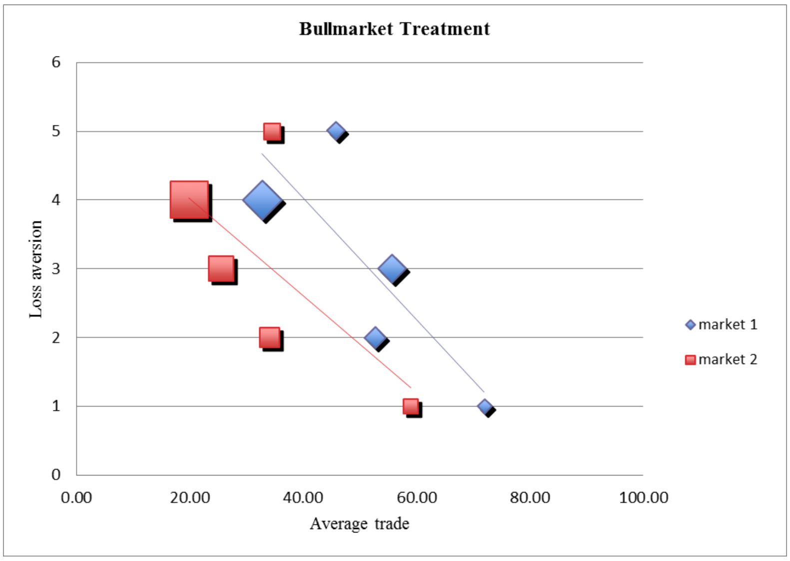
Figure 7: Final Individual Asset Holdings and Risk Aversion

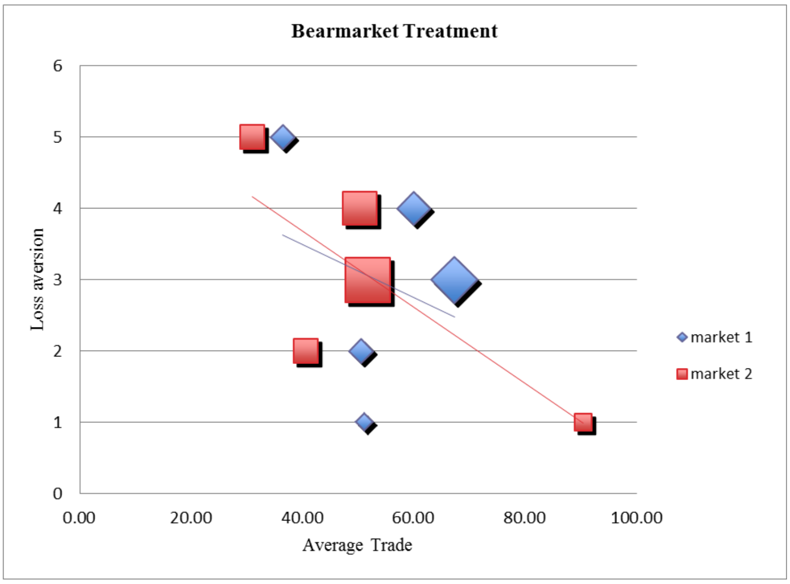




At first glance this last result seems inconsistent with the fact that the overall correlation between average risk aversion of a cohort and price level is greater in BullMarket than in BearMarket. However, the latter, a between-session correlation, is perfectly compatible with the stronger within-session relationship in BearMarket between individuals' risk aversion and their holdings. Figure 8 documents the relationship between loss aversion and individual trading behavior. The vertical axis shows the value of the loss aversion measure in part 1 of the experiment. Higher values indicate greater loss aversion. Loss aversion is plotted against the total number of units the individual trade, that is, the sum of her purchases and sales, over a 15-period market. Each data point is the average number of units individuals with a given loss aversion level trade over the course of their 15-period market.

Figure 8: Total Number of Trades Individuals Conculde and their Loss Aversion level

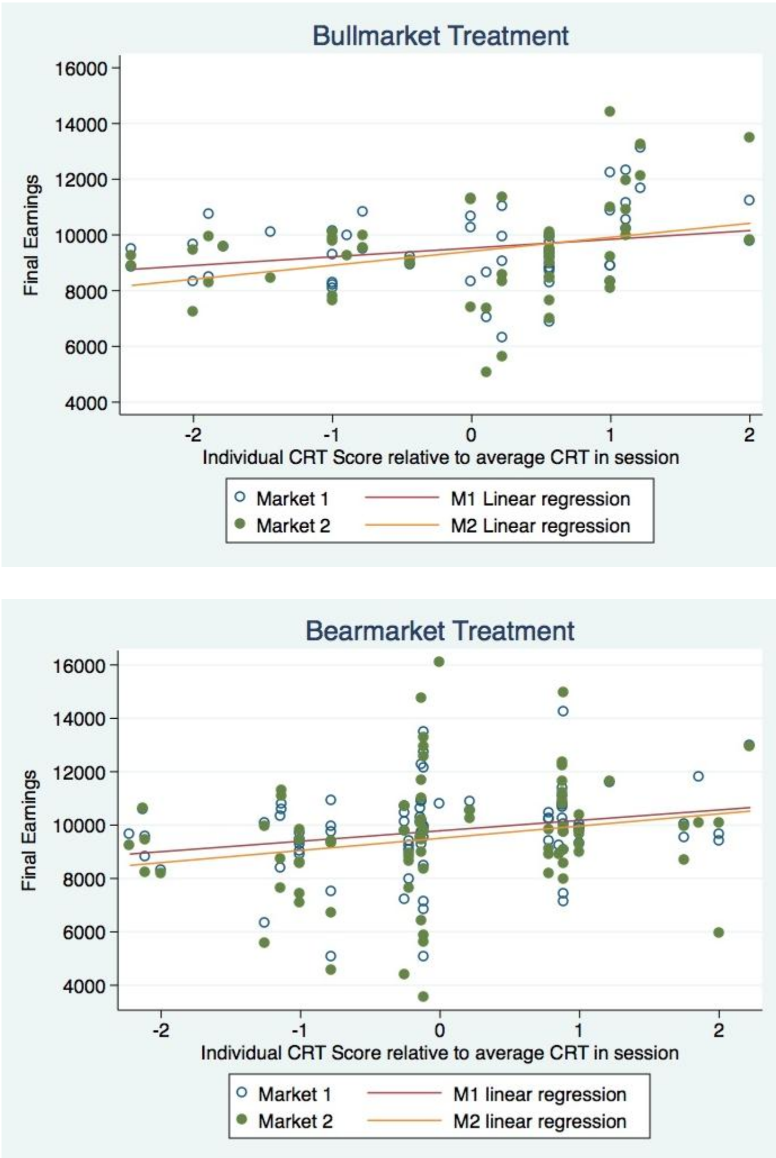




The figure shows, in the BearMarket treatment, a relationship between an individual's loss aversion and how much trade he engages in, with relatively loss- averse individuals involved in fewer trades. The correlation is -.180 (p = .035) in Market 1 and -.094 (p = .275) in Market 2. While this relationship does not appear significantly at the market level, in that a more loss averse group trades less than a relatively less loss averse group, it is clear that within a session, it is the less loss averse people who trade more. It seems that the relatively low number of observations at the market level and the greater presence of within- rather than between-group heterogeneity likely accounts for the lack of a significant relationship at the market level.

Figure 9 plots the CRT score of an individual minus the average for her session on the horizontal axis, and her earnings on the vertical. Each data point represents an individual participant. The figure shows that higher CRT scores are related to higher earnings. The correlations are highly significant for the Bullmarket treatment .291 (p = .000) and for Bearmarket treatment .285 (p = .009). In markets with a dispersion of CRT scores, those with lower scores earn less, indicating that they make unprofitable trades. In markets in which the average score is high, few traders make poor decisions, and prices stay relatively close to fundamentals.

Figure 9: CRT Score and final earnings at an individual level



4.2.2. Risk aversion, loss aversion, CRT score, and trader strategies

We now consider how the risk aversion, loss aversion, and cognitive reflection measures we have elicited correlate with trading strategies. To classify traders according to the strategies they tend to employ, we use the framework of Haruvy and Noussair (2006) and Haruvy et al. (2013). They classify traders into three types, called *Fundamental Value* Traders, *Momentum* Traders, and *Rational Speculators*. We classify each of the traders participating in our experiment as one of the three types, according to the following criteria.

We define an individual's behavior as consistent with the *Fundamental Value* Trader type in period t if either one of two conditions holds. The first condition is that, if $p_t > f_t$, then $s_{it} < s_{i,t-1}$, where p_t is the average price in period t, f_t is the fundamental value in period t, and s_{it} is the number of units of asset that individual i holds in period t. This means that if prices are above fundamentals, trader i is a net seller of units in period t. The second condition is that if $p_t < f_t$, then $s_{it} > s_{i,t-1}$. If prices are below fundamentals, trader i is a net buyer in period t. The fundamental value trader, then, acts as if she is using the fundamental value as a limit price.

A trader's behavior is consistent with the *Momentum* Trader type if either of two conditions holds. The first is that, if $p_{t-1} < p_{t-2}$, then $s_{it} < s_{i,t-1}$. The second is that, if $p_{t-1} > p_{t-2}$, then $s_{it} > s_{i,t-1}$. The momentum traders is a net purchaser in period t if there has been an increasing price trend in the last two periods, and sells off units if there has been a decreasing trend.

A trader's behavior is consistent with the *Rational Speculator* Trader type if her behavior in period t satisfies one of the following two conditions. The first is that, if $p_{t+1} < p_t$, then $s_{it} < s_{i,t-1}$, and the second is that, if $p_{t+1} > p_t$, then $s_{it} > s_{i,t-1}$. This type of agent anticipates the price in the next period in an unbiased manner. She makes positive net purchases if the price is about to increase between the current and the next period. She makes net sales if the price is about to decrease.

To classify a subject as one of the trader types, we count the number of periods during which a person is consistent with each type, and then classify him as the type with which he is consistent for the greatest number of periods. If there is a tie between two types, we classify the trader as belonging to each type with proportion .5. If there is a tie between all three types, he is assigned each type with proportion .33.

Table 1 shows the percentage of traders of each type in each treatment and market. It shows several interesting patterns. Despite the fact that the BearMarket treatment tracks fundamentals more closely than the Bullmarket treatment, the percentage of individuals classified as each type is very similar. Furthermore, the proportion of players of each type in market 1 is very similar to the two previous studies in which a similar classification was made for subjects with no prior experience in the same experiment (Haruvy and Noussair 2006, and Haruvy et al., 2013)[5]. The fraction of players that are Momentum traders decreases between markets 1 and 2 while the proportions that are of the Fundamental Value and Rational Speculator types increase. This change in distribution suggests that positive reinforcement is occurring, since momentum trading is irrational, resulting in relatively low earnings, while the other two types describe trading behaviors that reflect different notions of rationality.

Table 1: Proportion of Individuals of Each Trader Type, by Treatment and Market

	Market1		Market2	
	Flat FV	Increasing FV	Flat FV	Increasing FV
Fundamental Value	39.00%	33.33%	32.08%	34.91%
Momentum	28.61%	45.61%	28.30%	30.18%
Rational Speculator	32.39%	21.06%	39.62%	34.91%

	Market1		Market2	
	Flat FV	Decreasing FV	Flat FV	Decreasing FV
Fundamental Value	33.94%	39.97%	45.79%	44.00%
Momentum	30.92%	44.19%	20.47%	35.55%
Rational Speculator	35.14%	15.85%	33.74%	20.46%

[5] Both Haruvy and Noussair (2006) and Haruvy et al. (2013) classified 33.1% of their traders as Fundamental Value Traders, 25.4% as Rational Speculators, and 36.5% as Momentum Traders. Haruvy et al. (2013) categorized 40.1% of their participants as Fundamental Value Traders, 23.8% as Rational Speculators, and 36.1% as Momentum Traders.

Table 2: Correlation between trader type, risk aversion, loss aversion, and CRT score

Market 1	Fundamental Value	Momentum	Rational Speculator	Risk aversion	Loss aversion	CRT
Risk aversion	0.0228	0.0047	-0.0771	1		
Loss aversion	0.0775	-0.0902	-0.0337	0.1124	1	
CRT	0.2373***	-0.1934**	-0.0248	-0.0394	0.0990	1

*** correlation sig. at p< .01
** correlation sig. at p< .05

Market 2	Fundamental Value	Momentum	Rational Speculator	Risk aversion	Loss aversion	CRT
Risk aversion	0.1647**	-0.1446*	0.0259	1		
Loss aversion	0.1470*	0.0056	-0.1593*	0.1124	1	
CRT	0.1336	-0.2371***	0.0696	-0.0394	0.0990	1

*** correlation sig. at p< .01
** correlation sig. at p< .05
* correlation sig. at p< .1

Table 2 shows the correlations between risk aversion level, loss aversion level, CRT score, and each of the three types. Each individual trader constitutes one observation. The table reveals the following patterns. Cognitive reflection test scores exhibit a significant correlation with being a fundamental value type in market 1. This is consistent with previous results reported by Corgnet et al., (2012). CRT score is negatively correlated with momentum trading. These are intuitive relationships since momentum trading is an irrational strategy, while fundamental value trading requires the trader to interpret the future streams of dividends, final buyout value, taxes and subsidies as a limit price.

In market two, other intuitive relationships appear, perhaps because traders have had some time and experience so that they are able to formulate trading strategies that more accurately reflect their preferences. In market 2, there is a significant positive correlation between risk aversion and fundamental value trading. This relationship reflects risk-averse agents selling their units in large quantities when prices are greater than fundamentals. Loss averse agents are also less likely to be rational speculators in market 2, likely reflecting their desire to avoid the potential losses that one risks when speculating. There is no significant relationship between risk aversion, loss aversion, and CRT score, suggesting that they are largely orthogonal characteristics.

Table 3.a: Determinants of Average Dispersion with and without Risk Aversion, Loss Aversion, and CRT as Explanatory Variables

	Model 1	Model 2	Model 3	Model 4
Treatment	-24.04**	-17.21	-22.85**	-29.52***
Experience	-6.39	-6.39	-6.39	-6.39
Subject pool	31.66***			
Risk Aversion		13.74**		14.75***
CRT Score			-21.28***	-23.28***
Loss Aversion				4.79
	R^2 = 0.2464 N=32	R^2 = 0.1867 N=32	R^2 = 0.2665 N=32	R^2 = 0.4207 N=32

Table 3.b: Determinants of Average Bias with and without Risk Aversion, Loss Aversion, and CRT as Explanatory Variables

	Model 1	Model 2	Model 3	Model 4
Treatment	9.64	17.75	15.67	30.78**
Experience	4.73	4.73	4.73	4.73
Subject pool	-10.88	3.43		
Risk Aversion		-32.57***		-33.09***
CRT Score			19.25	21.84**
Loss Aversion				-2.41
	R^2= 0.0184 N=32	R^2= 0.3593 N=32	R^2= 0.0910 N=32	R^2= 0.4604 N=32

Tables 3a and 3b illustrate how much between-session variation in market prices that risk aversion, loss aversion and CRT score can explain. The dependent variables in the estimations reported in the table are the Average Dispersion and Average Bias. Model 1 includes the experience level of the subjects (whether the data come from market 1 or market 2), the treatment in effect, and the location in which the session was conducted. These variables explain 24% of the variance in AD and only 1% of the variance in AB. When the average risk aversion, loss aversion, and CRT score are added to the specification in model 4 (location is dropped because the different subject pools differ in the average level of CRT score), the explanatory power of the model increases substantially, to 42% for AD and 46% for AB. Thus, knowing the average risk aversion, loss aversion, and CRT score of a group of traders allows 46 times as much price level variation to be explained than when these measures are unavailable.

Furthermore, models 2 and 3 in each table are intended to capture the explanatory power of risk aversion alone and CRT score, respectively. We find that risk aversion explains more about the average bias as shown in model 2 from table 3.b, and the CRT score explains more about the average dispersion as shown in model 3 from table 3.a.

5. Conclusion

In this chapter, we have studied markets in which a trend in fundamentals sets in after an interval of constant value. Though the effect requires some trader experience before it sets in, prices tend to track fundamentals more closely when the trend is decreasing, in the BearMarket treatment, than when it is increasing, in the BullMarket treatment. The contrast between our results and those from previous studies indicate that the timing of the onset of a trend in fundamentals is an important feature influencing how the trend affects the price discovery process. This suggests that markets for assets which have a declining fundamental value trend from the moment of their creation, such as some bonds and options, or depreciating capital, might exhibit differences in pricing behaviour from those such as stocks and commodities that may experience episodes of declining value at later points in their lifetimes.

We observe correlations between risk aversion, loss aversion, cognitive reflection test scores, and market outcomes. The greater the average CRT score of the trader cohort, the less prices in their market deviate from fundamentals. Greater average risk aversion among the cohort of traders correlates with lower prices, though the effect is only significant for the BearMarket treatment. Risk aversion, loss aversion, and CRT scores, explain much of the between-session variation in market outcomes. It is already known that market parameters such as the amount of liquidity and the quantity of units of the asset available, as well as institutional features such as the availability of short-selling and of future markets, influence pricing in experimental markets. Our results underscore that trader characteristics are also important determinants of market behaviour. More risk-averse individuals are more likely to sell units and to trade on fundamentals. They are also less likely to trade on momentum. Loss-averse individuals trade less than their less loss-averse counterparts, and are less likely to speculate. Traders with higher CRT scores are more likely to trade on fundamentals and to achieve greater earnings. Traders with low CRT scores are more likely to be momentum traders.

Chapter2.

Emotional state and market behavior

1. Introduction

The connection between asset market price movements and emotions has been widely accepted in popular press and commentary. The supposed existence of fear and exuberance as influences on prices is reaffirmed with great frequency in such quarters. Positive emotion is generally associated with booms and high price levels. Alan Greenspan, while chairman of the Federal Reserve, famously remarked that the American stock market exhibited an “irrational exuberance” when it experienced a rapid run up in 1996. The remark betrayed a belief on his part that the increase had, in part, an origin in positive emotions of traders.[6] Galbraith (1984) describes stock market price bubbles as “speculative *euphoria*”. On the other hand, fear is associated with price variability and cited as a force leading to selloffs and price declines. Market volatility indices such as the CBOE’s VIX, an index of option prices, are referred to colloquially as “fear” indices. The legendary investor Warren Buffett (2008) writes, “A simple rule dictates my buying: be fearful when others are greedy and be greedy when others are fearful”, associating the presence of fear in the market with profitable opportunities to make purchases.

There is data supporting the contention that traders’ moods can lead to price movements at the market level. Hirshleifer and Shumway (2003) find that good weather is correlated with higher stock returns, while poor weather does not lower returns compared to average weather. They presume that the mechanism whereby this effect operates is through the positive effect that weather has on mood. Kamstra et al. (2003) observe that returns are relatively low in fall and winter and appeal to a similar intuition to explain their results. Sports scores seem to matter for financial returns (Edmans et al., 2007), with home team wins translating to higher prices. Bollen et al. (2010) find that Twitter mood predicts subsequent

[6] Our notion of happiness is a short-term emotional state, as distinct from a longer-term, more stable state of well-being. Bernanke (2012) clearly articulates this distinction. Happiness is a “Short-term state of awareness that depends on a person’s perceptions of one’s immediate reality, as well as on immediate external circumstances and outcomes. By "life satisfaction" I mean a longer-term state of contentment and well-being that results from a person's experiences over time.”

stock market movements. Gilbert and Karahalios (2009) find that the level of anxiety of posts on the blog site Live Journal predicts price declines.

In all cases, more positive emotional states are associated with higher prices. If emotions can increase prices, then they can in principle lead to mispricing well above fundamental values in some cases. In this chapter we focus on the connection between trader emotions and extreme pricing episodes: asset price bubbles and crashes. We use an experimental approach, which exploits the fact that bubbles and crashes can be reliably created and studied in the laboratory with inexperienced participants. The bubble and crash pattern was first observed in the laboratory with a paradigm introduced by Smith et al. (1988). Subsequent authors have replicated and established the robustness of this price pattern, and the Smith et al. (1988) design has become the dominant experimental paradigm for studying bubbles and crashes. We adhere to this design in the work reported here, and it is described in section three.

Bubbles can be eliminated in this setting when participants are inexperienced, but it requires a very strong framing that deemphasizes the importance of speculative possibilities or a considerable degree of specialized instruction. The magnitude of bubbles is sensitive to environmental parameters such as the amount of liquidity available (Caginalp et al, 1998), institutional factors such as the ability to sell short and the trading institution (Van Boening et al., 1993; Haruvy and Noussair, 2006; Lugovskyy et al., 2012), and the time path of fundamentals (Noussair et al., 2001; Noussair and Powell, 2010; Kirchler et al., 2012; Giusti et al., 2012; Breaban and Noussair, 2013). Nonetheless, there is considerable variation within all conditions that is unexplained. That is, some sessions generate larger bubbles than others despite identical economic structure. We consider here whether variation in the emotional state of participants between different cohorts can account for some of this heterogeneity.

In our experiment, we use face reading software to track the emotional state of all traders, as captured in their facial expressions. The software provides measures of happiness, surprise, anger, disgust, sadness, fear, neutrality, and overall emotional valence. According to Elster (1998) emotions can be differentiated from other mental states on the basis of six features: cognitive antecedents, intentional objects, arousal, valence, action tendencies, and physiological expressions. The work we report here focuses on the last feature, the physiological, as manifested in facial expressions. We consider several issues. First, at the market level, we study how emotional factors can influence the magnitude of bubbles. We test the hypotheses that a positive emotional state on the part of traders before a market opens predicts higher prices, and that fear predicts lower prices. At the individual level, we consider which emotions[7] are linked to better performance, and explore the relationship between loss-averse decision making and emotional state. Other than one concurrent study on individual decision making (Nguyen and Noussair, 2013), this study represents, to our knowledge, the first application of face reading in either economics or finance.

We find a number of strong relationships between emotions, as measured in traders' facial expressions, and market behavior. Positive emotion is associated with higher prices and larger bubbles. The more positive the valence of the emotions a group of traders exhibits before the market opens, the higher prices are in the subsequent market. Bubbles are driven by exuberance in the sense that at the individual level, making purchases during a boom is positively correlated with current valence. That is, individuals in more positive emotional states make more purchases during a boom. Those who exhibit more neutrality during a crash earn greater profits. We also observe a strong correlation between fear and loss aversion, as registered in a loss aversion measurement task administered before the market opens.

2. Previous literature

Moods have been linked to behavior in a number of well-known experimental paradigms, and some of these involve markets. For example, positive moods can influence product choices (Meloy et al., 2000) and bidding in random nth price auctions (Capra et al., 2010). Johnson and Tversky (1983) argue that a positive mood tends to make beliefs more optimistic in the sense that probabilities associated with positive events become distorted in a positive direction. This would push individuals to make less risk-averse choices when they are more positive emotional states. This suggests one mechanism whereby emotional state could influence market behavior. Asset markets involve the trading of a risky lottery and thus more risk-averse agents would tend to place lower value on the asset, and their activity would lead to lower demand and prices. Indeed, Breaban and Noussair (2013) find that more risk-averse cohorts of traders tend to generate lower prices in experimental asset markets. Fellner and Macjekovsky (2007) find that risk aversion on the part of a group of traders is associated with lower trading volume. Bosman and Riedl (2003) find that negative mood increases bidding in first-price sealed bid auctions, which is consistent with exhibiting more risk averse

[7] By emotion, we refer to short-term affective states. This is a distinct, though related, phenomenon to that of mood. See Capra (2004) for a discussion. While moods are of relatively low-intensity, diffuse, and enduring affective states without a salient antecedent cause, emotions are more intense and short lived, and they usually have a proximate cause.

behavior. Lowenstein et al. (2001), surveying a large body of research in psychology, argue that a direct link exists between decision making under risk and emotional state.

Fear, in particular, has been associated with risk aversion in a number of studies. Lerner and Keltner (2003) find that fear is associated with pessimistic risk assessments and anger with optimistic ones. Since pessimistic risk assessments lead to more risk-averse decisions with respect to objective risks, fear correlates positively with risk aversion. Kugler et al. (2012) obtain similar results in a different impersonal lottery based task. Nguyen and Noussair (2013) also find that fear in facial expressions is positively correlated with risk averse choices.

We are aware of three previous studies that explore the role of emotion in generating bubbles in experimental asset markets. All three papers consider markets with the structure of Smith et al. (1988), as we do here. Andrade et al. (2012) induce mood exogenously with film clips before the market opens. Subjects watch video clips that are (a) exciting, pleasant and arousing, (b) neutral, (c) fearful, or (d) sad. They find that the pleasantly exciting video clips are associated with larger bubbles than the other three treatments. The other three conditions are not different from each other in terms of average asset prices.

Lahav and Meer (2010) conduct an experiment with two treatments, which they call the positive and neutral treatments. Like Andrade et al., they induce mood by showing film clips to subjects before the market opens. Positive effect was induced with routines by comedian Jerry Seinfeld, and in the neutral treatment, no clip was shown. They find that the positive treatment is characterized by greater bubbles and higher prices than the neutral treatment, though the neutral treatment nonetheless generated price bubbles.

Hargreaves-Heap and Zizzo (2011) conduct an experiment in which emotions are tracked over the course of the session. They focus on anger, anxiety, excitement and joy. They have four conditions. In all conditions, subjects participate in two asset markets. In two of the treatments, individuals rate, on a Likert scale from 1 – 7, how intensely they currently feel each of the four emotions. In one of these conditions, subjects can chat with each other, and in the other they cannot chat. Hargreaves-Heap and Zizzo report that eliciting emotions does not in itself have an effect on market prices, but they do find that the level of excitement reported is positively correlated with price level. They also find that buying assets is linked to excitement and selling assets is connected to anxiety. They do not find a correlation between emotional state and trading profits. The work of Andrade et al. (2012), Lahav and Meer

(2010), and Hargreaves-Heap and Zizzo (2012) serves as the source of our first hypothesis, described in section four, that positive emotional valence on the part of traders is associated with higher prices.

Another of our hypotheses is inspired by a finding of Lo et al. (2005) and Lo and Repin (2002). These studies consider how emotions affect trading behavior and performance in a field setting. They follow a sample of individuals enrolled in a day trading course, and administer a survey to these traders after each day of trading. The survey asks several questions about emotional state. The authors report that those who exhibit emotions that respond more to short-term price movements in time periods of market turbulence earn less money and trade more than those who exhibit a weak emotional response. Taken to our setting, this would suggest individuals who have a more neutral emotional state during a crash have greater earnings.

3. The experiment

3.1 Experimental design and available data

The structure of the market was based on the paradigm created and studied in Smith et al. (1988). The asset that was exchanged in the market had a finite lifespan of T periods. At the end of each period $t \in \{1,\ldots,T\}$, each unit of the asset paid a dividend d_t that was independently drawn from a distribution that was identical for all periods. In any period t the expected dividend $E(d_t)$ on a unit of the asset was equal to the expected value of the dividend distribution. Dividends were drawn independently in each period. Therefore, the expected future dividend stream at time t, $E[\sum_t^T d_t]$, equaled the expected period dividend multiplied by the number of periods remaining in the life of the asset. In other words, $E[\sum_t^T d_t] = (T - t + 1)E(d_t)$.

Since dividends were the only source of intrinsic value for the asset, the fundamental value f_t had a particularly simple structure. It was equal, at any time t, to the expected future dividend stream from time t onward. In other words, $f_t = (T - t + 1)E(d_t)$. In our markets, the life of the asset was $T = 15$, and the dividend was $d_t \in \{0,8,28,60\}$, where each realization was equally likely, for all t. Thus, $E(d_t) = 24$, and $f_t = 24(16 - t) = 384 - 24*t$ at time t. The dividend distribution had a standard deviation of 27 per period, which was greater than the expected dividend. Therefore, risk-averse traders could value the asset at considerably less than its fundamental value.

In each period, each trader had the ability to trade units of the asset for cash with any other trader in an open market, provided that he always maintained non-negative cash and share balances. Transaction prices were determined in a continuous double-auction market (Smith, 1962). This type of market operates in the following manner. Each period, the market is open for a fixed time interval, which was two minutes in this experiment. At any time while the market is open, any trader can submit an offer to sell or to purchase a share. These offers are posted publicly on all traders' computer screens. Also at any time, any trader can accept an offer that another trader has submitted. When a bid or ask is accepted by a trader, a transaction for one share takes place between the trader who posted the offer and the trader who accepted it. Thus, within a period, it was possible for different transactions to occur at different prices. An individual could trade as much as he wished provided he has sufficient cash and units of the asset to complete the trades.

Each subject had an identical portfolio, consisting of an initial endowment of 5 units of asset, and 5000 units of experimental currency, at the beginning of period 1. A subject's final earnings in the market were equal to the cash he had at the end of the experiment, which corresponded to his initial cash, plus the value of dividends received, plus (minus) any profit (loss) from trading. The market was computerized and used the Ztree program developed at the University of Zurich (Fischbacher, 2007).

Prior to the opening of the asset market, we administered the loss aversion measurement task used by Trautmann and Vlahu (2007), which is based on an earlier protocol of Fehr and Goette (2007). This task consisted of a series of six choices, presented in a price list format. Each choice offered the opportunity to play a gamble which paid 4.5 Euro with probability .5 and either -0.5, -1.5, -2.5, -3.5, -4.5 or -5.5 Euro with probability .5, with each choice appearing exactly once. Subjects were required to indicate whether or not they accepted to play each of the six gambles. The number of gambles one decided not to play is interpreted as a measure of her loss aversion.

Subjects completed the task using pen and paper. They submitted all six of their decisions simultaneously when they turned in their completed sheet of paper to the experimenter. They were informed prior to beginning the task that only one of the decisions would count toward their earnings. After all decisions were turned in, a die was rolled. The outcome of the roll determined which decision would count for each participant. If a subject had chosen not to play the relevant gamble, she received a payoff of zero for this part of the experiment. If a participant chose to accept the selected gamble, a coin was flipped to determine whether she received 4.5 Euro or the negative payment specified in the gamble.[8] A separate coin was flipped for each participant who chose the gamble.

Our dataset consists of 13 sessions. The sessions were conducted at Tilburg University and all subjects were students at the university. Subjects were recruited via an online system. No subject participated in more than one session of the experiment. On average, the sessions lasted one hour. Between six and 11 traders participated in each session, with an average of eight subjects per session. Participants' earnings from the asset market were converted to Euro at a rate of 500 units of experimental currency to 1 Euro. This resulted in an average payment of 15.6 euros (including the loss aversion measurement task).

3.2. The Facereader software

Facereader operates in the following manner. The position of the face in an image is found using a method called the Active Template Method (ATM). This method places a template over an image and calculates the most likely position of the face. A second algorithm for face finding, the Viola Jones cascaded classifier algorithm, takes over when the Active Template Method cannot locate a face. A model called the Active Appearance Model (AAM) describes the location of 55 key points in the face and the facial texture of the convex hull defined by these points. The model uses a database of several thousand annotated images and calculates the main sources of variation found in the images. Principal Component Analysis is used to reduce the model's dimensionality. The classification of the facial expressions is done with an artificial neural network, which takes the vector of 55 locations on the face as input. The network was trained with roughly 2000 images of different individuals to classify the extent to which a face expresses the six basic universal emotions of happiness, surprise, anger, disgust, sadness and fear, as well as neutrality.

The output of Facereader is in terms of graphics and text. This software´s quantitative output is a vector of values for the seven emotions and an overall valence of emotional state. The possible values of each emotion range from 0 to 1, and valence ranges from -1 to +1. The

[8] Some subjects experienced real losses in this part of the experiment. However, they were informed that there would be subsequent activities in the session in which they could expect to earn money on average. No subject ended the session with negative final earnings, because income in the market phase of the experiment in all cases more than fully offset losses incurred in the loss aversion measurement task.

values are registered five times per second. Figure 1 illustrates an example of the output of Face Reader graphically. As the video is analyzed, the two charts on the right of the figure indicate, in real time in both bar graph and time series format, the extent to which each of the six basic emotions (as well as neutrality) is reflected in the facial expression. A pie chart, in the lower portion of the figure, shows the average intensity of each emotion. These values are normalized so that the sum over all emotions equals 1. The valence is an overall measure of whether the individual's emotional state is currently positive or negative. It is given as a time series in the upper middle portion of the screen. The measure compares the conformity of the facial expression to 'Happy', the only positive emotion, with that to the four negative emotions.

In the present work we do not test for the validity of this software as there are some methodology studies in the literature that are aimed to this purpose. There is evidence that Facereader output tends to identify the intended emotion of an individual with a high degree of success (Uyl and Kuilenberg, 2008). A recent marketing study by Lewinski et al. (2014) finds that the Facereader measure of happiness is highly correlated with participants' self-reports, even in a setting outside the laboratory. It also corresponds closely to observers' evaluations of the faces considered (Terzis et al., 2010).

This is the first study to employ face reading in experimental finance. In our opinion, face reading is especially well-suited to the study of emotions for several reasons. The first reason is that it classifies an individual's physiological state along emotional dimensions in a quantitative manner. This allows us, for example, to claim that one stimulus provokes more disgust but less sadness than another, or that a particular decision is taken when an individual is surprised rather than angry. A second advantage is that it registers emotional measurement in a manner that is completely unobtrusive to the participant, and data acquisition would proceed unnoticed if the individual were not informed that it was occurring.[9]

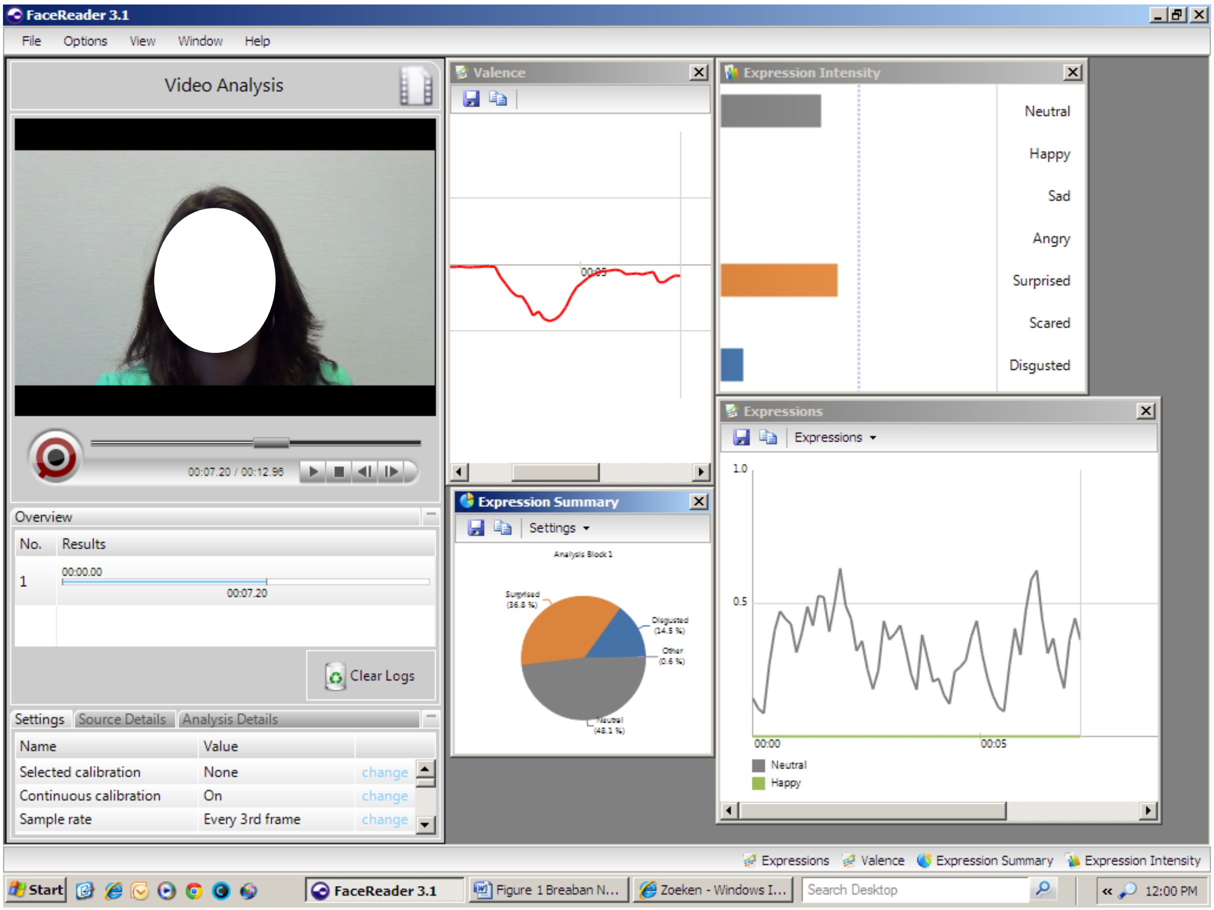
The third reason is that the facial expressions corresponding to the six basic emotions appear to be universal (Ekman and Friesen, 1984).[10] These expressions accompanying these emotions are common to all cultures and primates (Ekman, 1997). They are the same for blind and sighted individuals (Matsumoto and Willingham, 2009), which provides strong

[9] Subjects were aware that they were being videotaped but not that their videotapes were to be analyzed with facereading software.

[10] However, recent research on facial expressions and emotions shows that mental representation of the basic emotions is different across cultures (Jack et al., 2012). The main finding of this study is that Western Caucasian subjects represent each of the six basic emotions with a distinct set of facial movements common to the group, whereas Eastern Asian subjects do not. However, the extent to which such differences in mental representation of emotions are caused by actual different facial expressions is not obvious and needs further investigation.

evidence that they are innate. This means that results of studies such as ours should be replicable in different population groups and cultures. Happiness is positive in valence, surprise is neutral, and the other four are negative. Happiness and anger are approach emotions, which tend to lead an individual to move toward the situation that triggers the emotion. Sadness, disgust, and fear, are withdrawal emotions, meaning that an individual typically seeks to avoid the stimulus that induces these emotions.

Figure 1: Facereader Output



3.3. Procedure

Subjects were recruited via online system and the only restriction imposed was that wearing glasses during the experiment was not allowed.[11] They were randomly assigned to a computer number and handed the instructions for the first part of the experiment, that is, the loss aversion test. Instructions were then read aloud to them by the experimenter. They were informed that the experiment consisted of two parts and that possible losses in the first part of the experiment would be compensated by potential gains in the second one. Once they had completed the test with all six decisions, they handed in the sheet of paper on which they also provided the computer number they were assigned as well as age and gender. A volunteer subject then rolled the die which determined the lottery that was going to count toward their earnings. Given the die roll outcome, subjects who had decided to play the chosen lottery, then had to toss the coin to determine if they won or lost the amount specified in that lottery. The outcome of the coin flip was checked and registered by the experimenter.

The instructions for the second part of the experiment were then handed to subjects and read aloud by the experimenter. Once the general rules of the double auction market were explained, subjects had a five minutes practice period in which they could get familiar with buying and selling and submitting offers to buy and offers to sell. Following, they were explained the specific conditions of the market they were going to participate in, and questions and doubts regarding those were addressed.

The experimenter then informed all participants that during the rest of the experiment they were going to be videotaped by a video camera placed on top of their screen, and that the recording would only be viewed and used by the experimenter for research purposes. Subjects were also informed that it was important that they focus on the market, and that they avoid touching their faces or putting any obstacles between them and the camera.

We used a standard Logitech camera for each subject in the first eight sessions. New ones made by Microsoft were installed and used in the last five sessions. This allowed us to obtain better video quality and Facereader outcomes[12]. The video recording was started manually on each computer by the experimenter, and the Z-tree screen was then showed, so

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[11] This restriction was eliminated when Facereader 5 was available for the last 5 sessions, since the updated version of the software is capable now to analyze faces though glasses.

[12] The poor video quality in the first eight sessions had great negative impact on the analysis speed of the Facereader software. On average, the ratio was of one minute of video being analyzed in more than one hour, which made the task of collecting the data extremely slow. This was also the reason for which for the first eight sessions we only analyzed the boom period, the crash period and the 30 seconds before the market activity started. The better video quality allowed us to analyze the last five sessions at an average speed of 1 to 2 minutes.

subjects did not see themselves being videotaped. After at least 30 seconds have passed since the last video camera was turned on, the market started operating. In order to be able to match the timing of the video (since each video started at a different time and had a different length) with the market activity, we introduced a visual mark in each video that identified the moment at which the Ztree program had started. We did this by simply turning off and on the lights in the room at the moment the market started. The change in lighting was captured by all video cameras.

Later on, the videotapes were analyzed with Facereader software for the 30 seconds preceding the light mark which indicated the market opening, and for the subsequent part considering that every period lasted for 120 seconds. For the first eight sessions, the software was run for one video at a time using Facereader 3. For the last five sessions, we used Facereader 5 which allows for batch file analysis.

4. Hypotheses

We advance several hypotheses about the relationships between emotions and market behavior. Most of the hypotheses emerge from previous work. This first is suggested by the previous studies of Lahav and Meer (2010), Andrade et al. (2012) and Hargreaves-Heap and Zizzo (2012). We hypothesize that the more positive the mood[13] that traders exhibit before a market opens, the greater the price level in the market. Thus, we hypothesize that positive mood is positively related to subsequent price, and thus in all likelihood within our setting, to greater bubbles. This pattern is also suggested by previous work on auctions, which concludes that positive mood is associated with higher bidding (Capra et al., 2010). [14]

Hypothesis 1: More positive valence before the market starts, predicts greater subsequent prices and a larger bubble later in the session.

To test this hypothesis, we check whether there is a correlation between (a) the average emotional valence within a group of traders in the 30 seconds before their market

[13] For hypotheses 1 and 2 we use the notion of mood to refer to the initial emotional state (measured before the market starts) because it is not caused by any specific event. For the last two hypotheses we talk about emotions given that there is an interaction between emotions and specific events in the market.

[14] We interpret this hypothesis to mean that the market value of the good is greater when the individuals trading it are in a more positive emotional state. In a setting such as the bond market, in which trading can be made on price or on interest rates, a greater value of the good is associated with a higher price and a lower interest rate. If our hypothesis holds, in such markets a positive mood would lead to lower interest rates.

opens for period one, and (b) the average price over the 15 periods the market is open. Valence is a net measure of positivity of emotional state, or in this case, of mood.

We also consider whether fear predicts lower prices. That it should do so is intuitive. However, Andrade et al. (2012) fail to detect such an effect, and their attempt to induce fear generates similar results to a market in which emotions were not induced. However, Hargreaves-Heap and Zizzo do find that anxiety, a closely related emotional state, is correlated with lower prices. To the extent that fear is associated with risk aversion (see Lerner and Keltner, 2001, or Nguyen and Noussair, 2013), fear would lead to lower pricing of the lottery that corresponds to the price of the asset. Furthermore, it is possible that those who experience fear would be less likely to take on the risk associated with speculation, speculative demand would be reduced, and fear would have the effect of lowering prices.

Hypothesis 2: Greater fear on the part of the average trader before the market opens is correlated with lower subsequent prices later in the session.

Hypothesis 1 and 2 were concerned with the average valence and fear present before any activity has taken place. The next hypothesis considers the relationship between emotions and activity during a bubble. We consider the period during which prices exhibit the greatest average increase, and denote this as the *boom* period. If there is "exuberance" driving demand and pushing up prices during a bubble, the common view expressed by commentators, one would expect to observe those individuals who have more positive emotional valence during the boom period making the most purchases. Hypothesis three is that this pattern would appear in our data.

Hypothesis 3: Booms: During a boom, individuals with more positive valence make greater net purchases.

While hypothesis 3 relates to booms, hypothesis 4 has to do with the emotional correlates of crashes. Hypothesis 4 consists of three parts. The first has to do with the overall strength of emotions during a crash and trader profits. Lo and Repin (2002) and Lo et al. (2005) find that those who exhibit less volatility in their emotional state in the face of fluctuations in the market have greater earnings. In our experiment, the analogy would be a hypothesis that the level of neutrality in one's facial expression is correlated with greater trading profits. The second and third parts of the hypothesis concern the emotions associated with the rapid decrease in asset value that occurs during a crash. Those who have more units of asset incur greater losses during a crash than those with fewer units. We hypothesize that two distinct emotional episodes accompany a crash. During the market freeze-up and price decline, there is fear. This fear is presumably greater for those individuals who hold more units of the asset, as they have more at risk and are therefore losing more during the crash. At the end of a crash, there is less uncertainty and the consequences of the crash are known. Those who hold more units have incurred the greatest losses. Thus we expect the negative emotions that appear after adverse events: anger, disgust and sadness (fear appears in anticipation of a possible adverse event) to be positively correlated with how many units an individual holds at the end of a crash.

Hypothesis 4: Crashes: (a) Traders who exhibit greater average neutrality during a crash period achieve greater final earnings. (b) Traders who hold more units at the beginning of a crash period exhibit more fear on average during the period. (c) Traders who hold more units at the end of a crash period have experienced more anger, disgust, and sadness during that period.

5. Results

The time series of transaction prices in each of the eight sessions are shown in figure 2a, along with the time path of fundamental value. In the figure, the vertical axis is in terms of experimental currency, and the horizontal axis indicates the market period. As can be seen in the figure, there are large differences between sessions, but in most sessions the bubble and crash pattern is observed. Typically, prices remain above fundamental values for a considerable period of time, and then exhibit a rapid fall toward fundamental value.

Figure 2a: Average Transaction Price, All Periods, All Markets

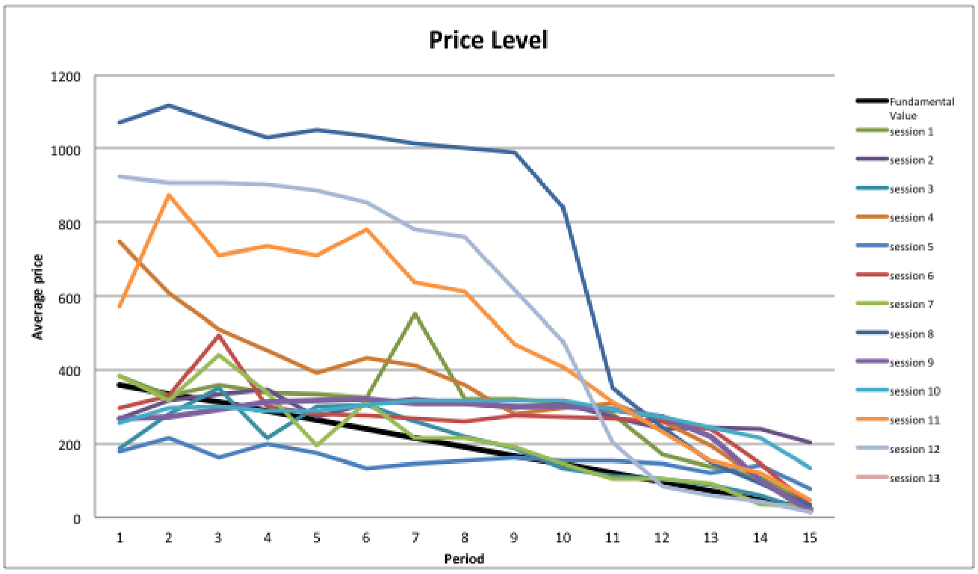


Figure 2b: Standard Deviation of Transaction Price, All Periods, All Markets

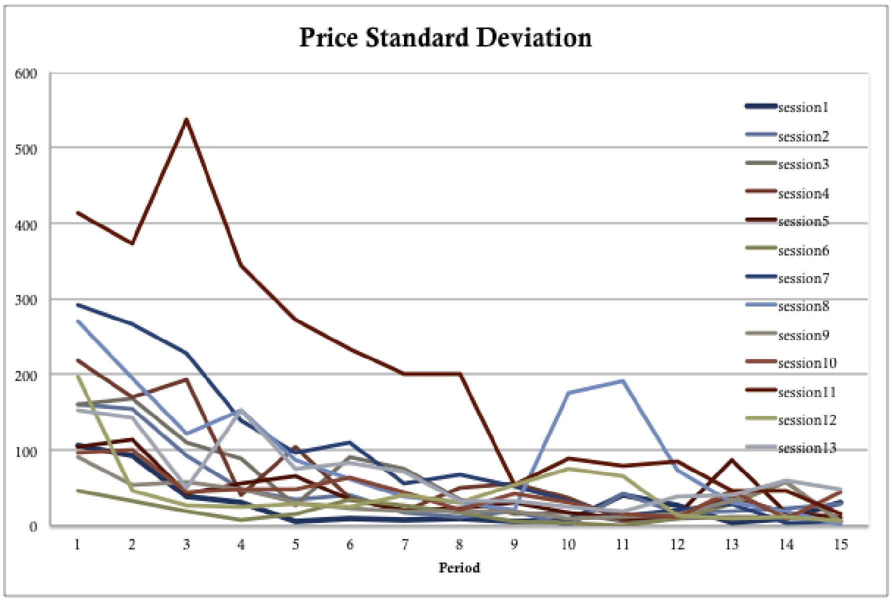
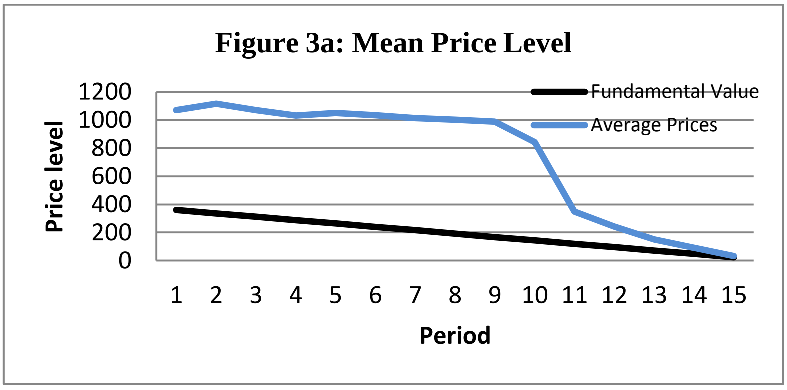


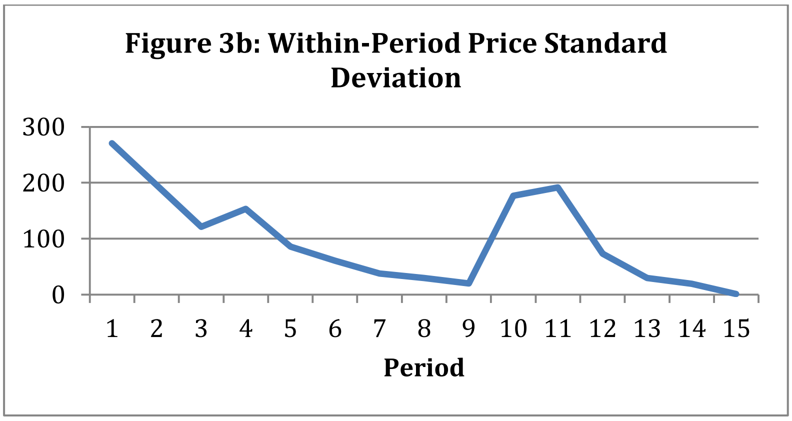
Figure 2b illustrates the standard deviation of transaction prices within each period, by session. Because the double auction market system allows trades to be concluded at different prices within a market period, the standard deviation of prices within a period can be substantial. This is especially the case during an episode of rapid price movement, such as a crash. The figure shows a consistent pattern. While the standard deviation differs by session, it tends to be greatest at the beginning of the life of the asset and during the crash. It is smallest near the end of the asset's life, when prices adhere relatively closely to fundamental values.

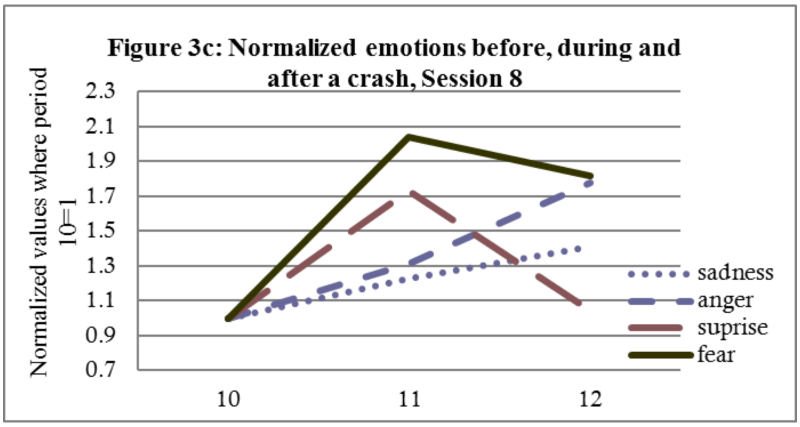
The relationship between a particular bubble and crash episode and the dynamics of emotion is illustrated in figures 3a – 3c. The data are from session 8, which exhibits a particularly large and obvious bubble and crash. The first two panels show that a crash occurs in period 11, and the crash is accompanied by a surge in price variance. In the third panel, the strength of the average level of several emotions that members of the session cohort exhibit over period 10 – 12, the periods just before and during the crash, is plotted. These emotions are anger, fear, happiness, and surprise. They are normalized at the levels observed in period 10, just before the onset of the crash.

The data show a clear pattern. Sadness and anger exhibit modest increases during a crash as traders' paper wealth declines. However, fear and surprise exhibit sharp increases, as uncertainty increases. By period 12, when the crash is ending, surprise has fallen sharply, and fear has decreased modestly. However, sadness and anger continue to increase, as traders realize the extent of the losses the crash has created. The figure illustrates the existence of an emotional reaction to a key market event and the ability of Facereader to coherently characterize this reaction.[15]

Figures 3a – 3c: Market 8, Time Series of Mean Transaction Price, Standard Deviation of Price, and Emotions







[15] The facial expression data exhibit several broad characteristics. The first is that the valence is typically negative. This likely means that participation in experiments yields disutility for participants compared to other activities. There is great volatility in emotional state even over short time intervals. This may reflect the large number and heterogeneity of events that one experiences in a period. There is no discernible decline in the overall strength of emotion over time, over the roughly 35-minute period the asset market is in progress. Anger tends to be greater at the outset, possibly reflecting the fact that individuals who are concentrating tend to look like they are angry (see Zaman and Shrimpton-Smith, 2006), but within a few minutes it stabilizes. Valence reflects this pattern, typically being very negative at the very beginning of a session but stabilizing at a moderately negative level for the rest of the session.

We now evaluate the hypotheses advanced in section three. The first two hypotheses are about the relationship between the initial emotional profile and the overall price pattern, and are summarized as results 1 and 2. Here we use the average emotional state of traders over the 30 seconds prior to any market activity, in order to compute a baseline measure of the subjects' mood rather than an emotional response to a certain stimulus. An alternative metric of aggregate emotional state would weight each individual´s emotional state by the number of trades or perhaps by the number of offers they make. However, all players are in an identical position before the market opens, and the purpose of the measure is to predict beforehand what the market price level will be without the influence of the market activity on traders emotions. In chapter 3 we study the relation between individual emotional state and price movements in detail.

Result 1: A more positive mood before the market opens is positively correlated with subsequent market price level.

Support for Result 1: We take the average valence that Facereader measures over the 30-second interval before the market opens for each subject. We then average it for all subjects in a session. Then we correlate the average for a session with the average amount that price exceeds fundamental value over the course of the session[16]. Figure 4 below plots the average initial group valence against the average price level over the 15-period life of the asset. The figure shows a clear positive relationship between mood and price. The Spearman correlation between valence in a session and average price level in the session is $\rho = 0.708$ ($p = .01$).[17] □

[16] The same results would obtain if we used the average price difference from fundamentals $p_t - f_t$. This difference is referred to as the *Bias* in a market by Haruvy and Noussair (2006).

[17] The correlation between the variance of valence among participants before a session begins, and the volume of trade over the entire session, is .12, and is not significant at conventional levels.

Figure 4: Valence Prior to Market Open and Price Level

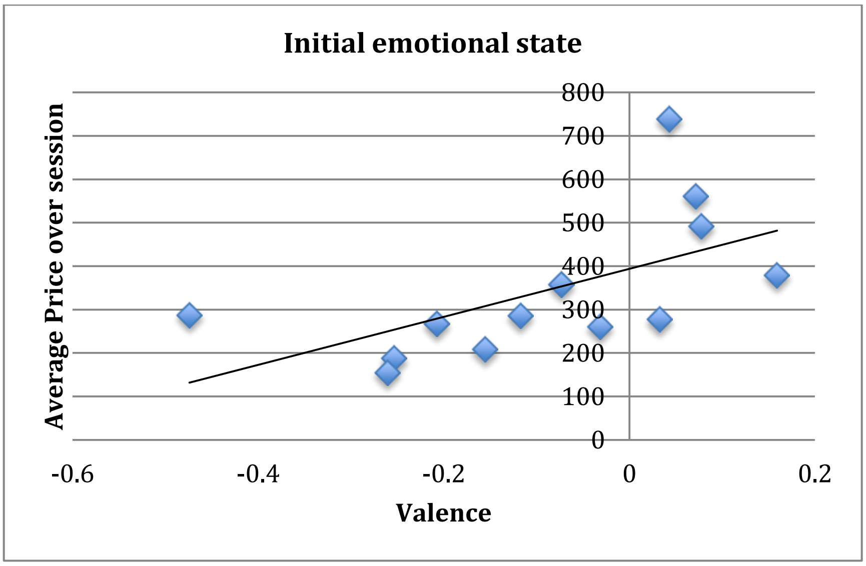
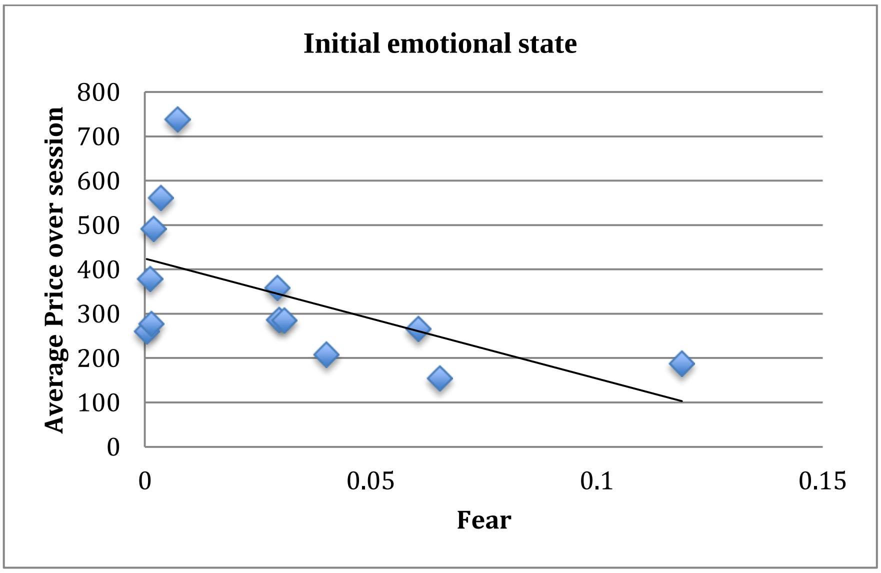


Figure 5: Fear Prior to Market Open and Price Level



Result 2: Average trader fear before the market opens is negatively correlated with the subsequent price level in the market.

Support for result 2: The relationship between the average fear a cohort expresses before the market opens and price level over the subsequent market is very pronounced. Figure 5 relates the fear that Facereader registers in the average trader in a given session to the average price in the session. The figure shows a strong negative relationship between the two variables. The correlation is highly significant (ρ = -0.549, p = 0.06). □

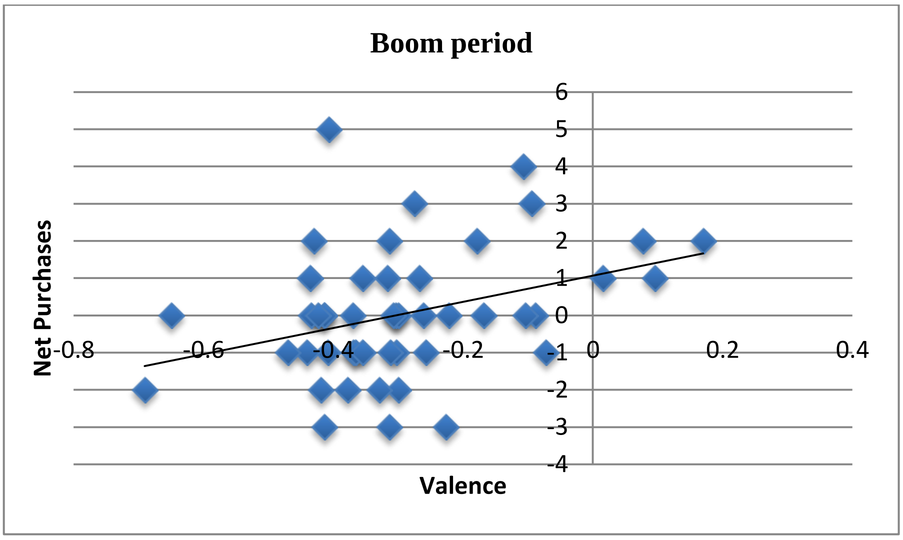
Indeed, all the other emotions considered separately also correlates with subsequent price level. The three negative emotions, sadness, anger, and disgust, correlate negatively with price level at ρ = -.381, -.428, and -.333, respectively, while happiness and neutrality correlate positively with price level at ρ = .476 and .357. While none of these correlations are significant, they are consistent with higher (lower) prices being associated with positive (negative) emotional states.

One of the mechanisms through which emotions affect market behavior and subsequent prices might be the expectations that traders form regarding future dividends and prices. Therefore more optimistic prior beliefs on the part of the average trader in a market could improve her mood leading to more purchases and higher prices. Similarly, pessimistic beliefs before the market opens might lower prices later in the market through the emotional channel of fear. In our experimental design expectations are not elicited, though future research could do so with the aim of establishing such a relationship between emotional state and expectations. A dynamic interaction could be at work since expectations affect emotional state in a market as well as the emotions could interfere in the process of forming expectations. Emotions and expectations, together with opportunity sets and market circumstances, might all be components of an investor's sentiment.

For hypotheses three and four, we consider the average emotional state for each subject during the boom and crash period, respectively. We then compute the average emotional state for each session.

We now consider hypothesis three, which relates individuals' emotional valence to their behavior during a boom. The boom period of a session is defined as the period with the greatest net price increase over the immediately preceding period, that is, the period t that maximizes $p_t - p_{t-1}$ within a session. Figure 6 shows the level of valence on the horizontal axis for each individual in the eight sessions, and the net change in her holding of shares within a period. The data are from the two-minute boom period of each session. The figure suggests the pattern described in result 3.

Figure 6: The Relationship between Individual Emotional Valence and Net Purchases, Boom Period



Result 3: During a boom, valence is positively correlated with net purchases

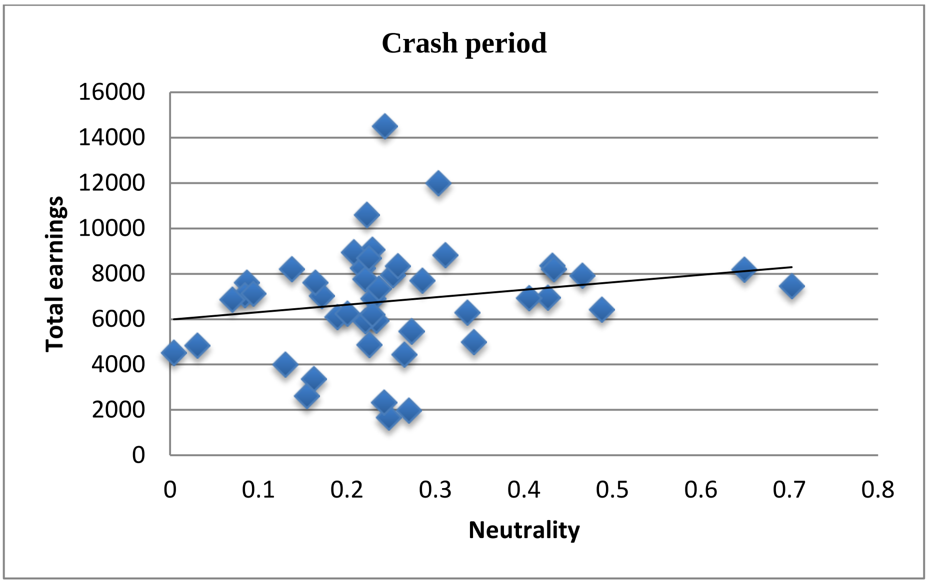
Support for result 3: The correlation between v_{it}, the valence of individual *i* in period *t*, and $s_{it} - s_{it-1}$, the next purchases of individual *i* in period *t* (s_{it} is the quantity of asset individual *i* holds at the end of period *t*) during the boom period is 0.323 (p = 0.026). The current cash endowment could be affecting both valence and purchases positively, though our results do not show such an effect. The correlation between m_{it-1} (cash at the beginning of period *t*) and v_{it} is equal to 0.0007 (p=0.996) and the correlation between m_{it-1} and $s_{it} - s_{it-1}$ is -0.03 (p= 0.796).

A number of interesting related patterns also appear in the data. The correlation between happiness and net purchases in the boom period *t* is also significant (ρ =0.3010, p = 0.04). However, the correlation between net purchases in the boom period and fear is close to zero (ρ = 0.0188, p = 0.9). Average valence is not greater on average during a boom than at other times. Before the market opens it averages -.18, during the boom period it equals an average of -.29, and during crash it is -.28.

Given the positive relationship found between emotional state and asset holdings during a boom period, we further considered the possible relationship between the individual's mood before the market open and their final asset holdings at the end of the experiment. No significant relationship was found though between initial valence and fear and final holdings, indicating probably that mood does not predict individual trading strategies on a long run, but emotions are closely related to decision making in the short run and especially in high prices environments.

The first part of the hypothesis four is that more neutrality during a crash is correlated with greater average earnings. Figure 7 plots the relationship between the level of neutrality individuals exhibit during a crash period, which we define as the period with the greatest price decrease from the preceding period, and the final earnings an individual accrues over the entire 15-period market. The figure suggests that more neutrality during a crash is correlated with better performance. The support for result 4 confirms this impression. In addition, the hypothesis postulates that at the individual level, the number of units held during the crash period, which measures the amount of paper losses incurred during the period, correlates with the four negative emotions. However, we observe that none of these negative emotions is related to the extent of these losses.

Figure 7: Relationship between Neutrality and Earnings, Crash Period



Result 4: Traders who exhibit greater neutrality during a crash achieve higher earnings.

Support for result 4: The correlation, at the level of the individual, between her average neutrality during the crash period and her final earnings is 0.205 (p = 0.16). Neutrality correlates negatively with units held at the end of the crash period at ρ = -.27 (p = .064). The other emotions do not correlate with the number of units held, and thus the amount of unrealized capital losses, during a crash. The results are similar if the units held at the beginning of the crash period are considered (very few units are exchanged during a crash because of very low demand). □

The last result, five, describes a strong correlation between loss aversion and fear. The loss aversion protocol that was administered at the beginning of the sessions, and the measurement of the emotional profile of individuals before the market opens, permit an analysis of the correlation between loss aversion and the emotional state of participants at the individual level that is independent of any experience on the market. As summarized in result 5, those who make more loss-averse decisions exhibit more fear in their facial expressions, and have a more negative overall emotional state. There is no correlation between loss aversion and any other of the six basic emotions or with neutrality.

Result 5: Individuals who exhibit more fear make more loss-averse decisions. Loss aversion is not significantly correlated with anger, happiness, sadness, disgust, surprise or neutrality. Loss aversion is negatively correlated with the valence of emotional state.

Support for Result 5: Table 1 contains the correlations between the number of gambles declined in the loss aversion task and the average consistency of facial expressions with each of the six emotions that Facereader registers in the 30 seconds before the market opens. A greater number of gambles declined indicates greater loss aversion. The table shows that the correlation between fear and loss aversion, .3427, is positive and significant at the $p < .05$ level. The correlation between loss aversion and valence is negative (ρ = -.3012, $p < .05$). In contrast, none of the correlations with other emotions are significant at even the 10% level. □

We now study the feedback between an individual's performance in the market and her emotional state. Define the value of an individual's asset/cash position at any point in time as $w_{it} = c_{it} + p_t s_{it}$, where w_{it} is an individual's wealth at time t, c_{it} is the cash that i has at the end of period t, and s_{it} is the quantity of units he holds. We conjecture that valence, as well as happiness, would be positively correlated with current wealth, which can be measured as the level of cash the player has at present, plus the market value of one's shares. Of course, it is possible that emotional feedback occurs exclusively through the price level or through cash holdings, and in that case the correlation would be only present for c_{it} or p_t. We also conjecture that a subset of the negative emotions of fear, anger, disgust, and sadness, evaluated at time t, would be negatively correlated with wealth at time t. The regression reported in table 2 considers these effects, and is the basis for result 6.

Table 1: The Correlation between Loss Aversion Measure and Emotional State

	Fear	Valence	Happiness	Anger	Surprise	Disgust	Sadness	Neutral
Loss aversion	0.342***	-0.301**	-0.045	-0.068	-0.085	0.209	0.109	-0.198
	(0.018)	(0.025)	(0.759)	(0.649)	(0.569)	(0.157)	(0.463)	(0.180)

Table 2: Emotional Correlates of Wealth, Cash Balance, Price Level, Volatility, and Gender

	Valence	Happiness	Anger	Fear	Surprise	Disgust
Wealth	.00008***	.00004**		-.00006*		
Cash				-.00001**	.00015***	
Price level	.00012***	.00007***	-.00006**		-.00079**	
Price volatility						
Gender	.06452**			-.05118**	.81038***	.07482***

Number of observations: 55

Result 6: Greater wealth is correlated with more positive emotional valence. Decomposing this effect into component emotions reveals that price level is positively correlated with happiness, while negatively correlated with anger. Lower cash holdings are associated with more fear.

Support for Result 6: Table 2 shows all of the significant effects of current wealth, price level, price volatility and gender on each emotion. Overall valence is influenced by wealth and price, with greater wealth and higher prices associated with more positive valence. Controlling for market variables, women have more positive valence than men. Greater wealth is associated with more happiness and less fear. Lower cash balance is correlated with more fear. Women are less fearful than men. While price volatility is positively correlated with fear, the relationship is not significant in this regression.

It seems straightforward that money and units are positively related to valence, since they can be considered as indicators of wealth. However, they also correspond to greater opportunities to buy and sell (Friedman et al. (2011)) and this might also be a cause of more positive valence. While higher cash and asset holdings expand the opportunity set, asset price level changes the opportunities available for a trader depending on their current cash and asset holdings.

6. Conclusion

In this chapter, we study the connection between emotions and asset market prices. We find a number of patterns that conform to commonly expressed intuition about the link between emotion and asset prices. When traders are in a more positive emotional state at the time the market opens, asset prices are higher. When they feel more fear, prices are lower. Traders in a relatively positive emotional state are the ones making purchases during a boom. Those who keep a neutral emotional state during a crash earn greater profits.

A number of factors have been shown to influence the incidence and magnitude of bubbles in the laboratory. These include the institutional structure, the time path of fundamentals, and the risk aversion, loss aversion, and cognitive ability of traders. The results reported here show that another factor can be added to the list; the emotional state of traders. This finding is in agreement with similar results that have recently been obtained (Lahav and Meer, 2010; Andrade et al., 2012; Hargreaves-Heap and Zizzo, 2012). Thus, it is becoming clear that asset price bubbles in experimental markets are a complex phenomenon, subject to many determining influences.

We find a strong correlation between fear and loss aversion. Such a connection is, in our view, quite natural and intuitive. Those who anticipate that they will have a more negative response to a financial loss exhibit more fear when placed in a situation in which losses are possible, and thus make decisions in such a manner as to minimize the likelihood of their occurrence.

This study is the first application of face reading to experimental finance. This methodology had yielded what are, in our view, coherent results. Our view is that the strength of our results contributes to the validation of the methodology. We believe that Facereading has considerable potential for the study of markets. In starker experimental settings than the one studied here, the emotional response to specific events, such as to a price quote one has received, or to a specific transaction one has made or observed, can be isolated and studied. In particular, in future work, face reading can be used to study face-to-face market transactions. In such situations, facial cues are important sources of information about the intentions and emotional states of other parties to a potential transaction. In these settings, individuals may try to manipulate their facial expression as part of their strategy to obtain more favorable terms. Face reading technology is highly conducive to the study of such behavior.

Chapter 3.

Micro-level data analysis on emotions and trading activity

1. Introduction

Stock market traders are usually imagined and depicted as emotionless calculating machines, like Gordon Gekko. This character of the late 80s was portrayed as a ruthless, successful and greedy businessman of Wall Street that showed no emotions when trading in the stock market. In his talks he seemed to encourage an emotionless, unscrupulous and selfish attitude among young investors as the way to succeed. Indeed, there is some empirical evidence on emotions affecting performance in financial markets. Lo et al. (2005) and Lo and Repin (2002) find that traders who exhibit emotions that respond more to short-term price movements in time periods of market turbulence earn less money than those who exhibit a weak emotional response. However, traders are human beings after all, which means emotions are a relevant variable in the asset markets.

In this chapter we analyse the dynamic relationship between emotions and market activity, at both the individual and market levels. In particular we are interested in a micro-level analysis, in terms of individual decisions and in terms of short time period, to provide a better understanding of the interaction between emotions, market variables and individual decision making. It seems reasonable to believe that there is a feedback process occurring between these variables in the sense that emotions affect individuals' behaviour, which then has an impact on market activity and on individuals' wealth, which in turn provoke emotional responses from traders. We try to identify the causal relationships of these effects in this chapter.

This chapter is organized as follows: the data set and methodology are described in section 2, followed by the hypothesis we wish to test in section 3. The results we find are discussed in section 4, and some commentary and conclusions can be found in section 5.

2. Methodology

For this analysis we use the data from five of the sessions described in the second chapter. In total, 50 subjects participated in these sessions and all of them were students at Tilburg University. Subjects were recruited via an online system. No subject participated in more than one session of the experiment. Between eight and 11 traders participated in each session, with an average of 10 subjects per session.

The reason to include only these five sessions in this chapter is purely technical. Due to an improvement introduced in the video quality in late 2013[18], in these five sessions it was possible to analyse all videos for the entire duration of the experiment. Therefore, for all 50 subjects it was possible to match their trading activity with their emotional responses. This allows for an analysis of the dynamics between emotions and asset market behaviour establishing causal relationships both at individual level and market level.

Data description

For the analyses presented in this chapter we use two types of data set. First of all we consider *tick-by-tick* data (where each tick is a 10 seconds interval) for the individual behaviour analysis. The setting used is a panel data in which 50 subjects are the cross-sectional data, and a 10 seconds interval is implemented as time series, which means that the time span of the experiment is a total of 202 intervals. The reason to specify the time variable as blocks of 10 seconds is the specific character of emotions. Emotions arise as a consequence of some events and last for a few seconds. There is little evidence in the literature on emotion duration, but Sonnemans and Frijda (1994) find that it depends to a great extent on the intensity of the emotion. Scherer et al.(1986) find that different emotions tend to have different duration and they classify sadness as the most lasting one, followed by joy, anger and fear. Given that the market experience is relatively short (one period lasts 120 seconds) and making decisions might take up to a few seconds, we expect that a 10 second interval is enough to capture both emotional and behavioural reactions to specific market events as well as short enough to capture the reaction to current activity only.

[18] New video cameras with higher resolution were used.

Therefore each emotion variable (happiness, fear, anger, disgust, sadness, surprise, neutral and valence) was averaged every 10 seconds beginning with the market opening, so that 300 observations that Facereader software provides (30 per second) were averaged for each subject. We will refer to the time variable in this data set as *intervals* in order to distinguish it from the time variable named *period* in the second data set.

Second, we construct a data set that gathers observations for 50 subjects during 15 periods. In this case the emotion variables were averaged over the 120 seconds of each period and subject.

Some descriptive data is shown in Table 1a on the emotions variables across the 202 intervals. There are two interesting features to be pointed out. One is that the average valence across subjects and intervals is negative, which indicates that subjects do not perceive experiments as a positive experience. If we compare the average valence in each period, we find that in 77% of the periods the average valence is negative. The second is that neutrality is a dominant emotion on average.

Table 1a. Emotions Descriptive data

	Neutral	Happy	Sad	Angry	Scared	Disgusted	Surprised	Valence
Observations	10020	10020	10020	10020	10020	10020	10020	10020
Min	0	0	0	0	0	0	0	-.977
Max	.995	.996	.977	.947	.385	.853	.991	.990
Mean	.524	.092	.083	.038	.001	.012	.021	-.029
Std. Dev.	.305	.153	.128	.091	.007	.054	.067	.231

The Facereader software calculates emotional valence by subtracting the value of the highest negative emotion from the value of happiness. Within our sample, valence is positively correlated with happiness (.706), surprise (.040) and neutrality (.024) and negatively correlated with sadness (-.535), disgust (-.284), anger (-.171) and fear (-.081). All correlations are significant at 1% level.

Regarding the trading activity, on average there are 33% more offers to sell than to buy, and only half of the offers to sell turn into actual trades, as shown in the following table. On average there is a trade taking place every 6 seconds.

Table 1b. Trading activity data in a period

	Nr. Trades	Nr. Bids	Nr. Asks	Avg Prices
Min	8	12	18	14.53
Max	47	82	117	923.33
Average	20.45	34.04	45.22	396.73

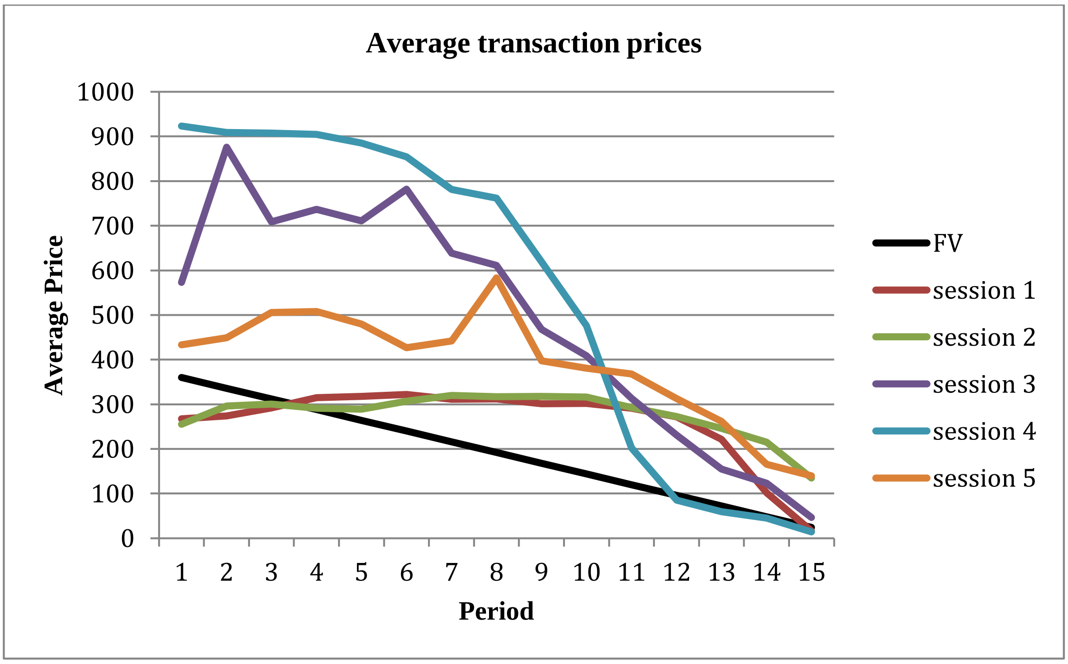
In table 1c below, it is shown that the sample is gender balanced with a total number of 27 females and 23 males and they were all Economics or Business students.

Table 1c. Subjects´ profile by session

Session	Female/Male	Average Age	Average loss aversion
1	5/5	22.7	3.2
2	4/4	23.7	3.5
3	6/4	24.1	2.8
4	7/4	22.0	4
5	5/6	23.1	3.5

The time series of transaction prices is shown in Figure 1 together with the fundamental value time path. It is clear that in all of the sessions large bubbles and subsequent crashes occur and in some of them prices are twice or even three times higher than the fundamental value of the asset. Typically transaction prices are always above fundamentals for a considerable length of time and towards the end of the experiment they rapidly fall towards fundamentals.

Figure 1: Transaction Prices and Fundamental Value Time Path



3. Hypothesis

Based on the results we obtained in the previous chapter and on accepted economic intuition, we advance several hypotheses about the interaction process between emotions and individual behaviour, as well as between emotions and market variables.

At the individual level, we have so far established a positive correlation between average happiness and the number of purchases during a boom. This is already an important result since it is the first connection found between emotions captured through physiological responses and market activity, though no causality in that sense could be established with the available data.

It is plausible to conjecture that positive valence causes purchases, due to more optimistic beliefs or a less risk averse attitude generated by a positive emotional state. This conjecture is in line with the affective generalization hypothesis of Johnson and Tversky (1983) that addresses the role of affect in judgments of probabilities. They argue that negative emotions trigger more pessimistic risk assessments, while positive emotions entail more positive risk assessments, and this leads individuals in a more positive mood to take more risk. Following this argument, in this chapter we hypothesise that a positive emotional state at any time in the market will cause greater net purchases in the moments immediately following.

Hypothesis 1a: A more positive emotional state at time t-1 makes individuals more likely to make purchases at time t.

Also in the previous chapter we hypothesised that traders who owned more units would experience more fear at the time of a crash. We found no evidence to support this hypothesis. The argument behind it was that the crash would actually occur because fearful people would attempt to sell, and often succeed in doing so, pushing prices down. Based on this argument we state the following hypothesis:

Hypothesis 1b: Individuals experiencing more fear at time t-1 will be more likely to sell their units at time t.

Besides purchases and sales, there are other behavioural patterns in the market that could be explained by emotions. The decision to submit offers to buy or to sell might also depend on the emotional state of traders. It seems reasonable to believe that if traders base their trading decisions at least partly on emotions, more neutrality on the part of traders would lead them to be less active in the market. That is to say, more emotional agents will intervene more by submitting offers to sell or offers to buy. Our second hypothesis, therefore, would be that this pattern would appear in the individual level data.

Hypothesis 2: More neutral individuals at time t-1 are less active in the market, in that they submit less offers at time t.

An interesting pattern was found in chapter 1 when matching individuals´ characteristics and their trading strategies, and it is that a higher CRT score was positively correlated with the fundamental value trader type and negatively correlated with momentum type. This, as we already mentioned, seems to be in line with the argument that more sophisticated traders are more likely to interpret the future streams of dividends as a limit price and therefore act as a fundamental value trader type. We further want to investigate if emotions could be playing a different role on traders´ behaviour depending on the trader type. We would expect that momentum traders, who behave irrationally and earn less money than the other two types, would be more influenced by emotions when trading, while fundamental value traders and rational speculators would be less swayed by emotions.

Hypothesis 3: Momentum traders´ decisions correlate with emotions more than those of fundamental value traders or rational speculators.

The first three hypotheses we have formulated concern the effect of emotions on individual behaviour in terms of sales, purchases or making offers. In turn, decisions and their subsequent outcomes have an impact on traders´ emotional state. Therefore our fourth hypothesis is about the second part of this process. A very natural intuition points to a more positive emotional state when the overall financial position of a trader improves.

Hypothesis 4: A better financial overall position at time t-1 improves the emotional state of a trader in the next time t.

On the other hand, traders could also have short-term emotional responses to specific actions such as buying and selling and the extent to which a purchase or sale has been profitable or not. Our fifth hypothesis is therefore about specific actions having an immediate effect on emotions.

Hypothesis 5: A profitable trade at time t-1 has a positive immediate impact on emotions at time t.

The following two hypotheses consider market level data. We have concluded so far in the previous chapter that, at the market level, a more positive initial state on the part of traders predicts higher prices and larger bubbles, and that more initial fear predicts lower prices and smaller bubbles later in the session. We further investigate whether this hypothesis is sustained in a continuous manner, that is to say, if happiness consistently enhances higher prices over time or if fear always predicts lower prices in the immediate subsequent periods. In the context of the 15 periods the market is open, we hypothesize that more fear in one period would predict decreasing average prices in the next period, and that more positive emotional state would on average predict higher prices in the following periods.

Hypothesis 6: At the market level, more average fear in one period predicts price decreases in the next period; a more positive emotional state predicts price increases in the next period.

Another dimension of the asset market is the volume of trade. Our next hypothesis is about whether an emotional component can be linked to a lower volume of trade. Based on the idea that a more positive emotional state makes individuals buy more and negative emotions such as fear makes them sell, we expect that, when a market is formed by traders with different emotional profiles, there will be more trades concluded.

Hypothesis 7: Higher variance of the emotional state of traders in a market correlates with a higher volume of trade.

4. Results

We now evaluate the hypothesis advanced in the previous section. The first five hypotheses concerning individual behaviour will be tested using tick-by-tick individual level data as we described in section 2. For the last two hypotheses regarding market behaviour, a data set, in which each observation is a market period, is used.

Result 1a: Traders with higher valence at time t-1 make more purchases at time t

Support for result 1a: In order to determine how emotions affect individual trading activity we run a Poisson count regression with subject fixed effects where the dependent variable is the number of units a subject has bought or sold during each 10 seconds interval. Each transaction is considered at the time at which a bid or an ask has been accepted. In particular we look at the influence of the past overall emotional state controlling for financial position and price level. We find that subjects are more likely to make more purchases in the current interval, the higher valence they exhibited in the previous interval. Table 2 below shows that introducing the lagged value of purchases in Model 1, higher emotional valence Granger-causes purchases[19]. It is also an intuitive result that the larger the number of units in inventory, less likely it is for subjects to buy more.

Result 1b: More fearful traders at time t-1 do not sell more units at time t

Support for result 1b: On the other hand, controlling for the units and cash they had and considering how high average prices are compared to fundamentals, we do not find a significant effect of the lagged value of fear over current sales, although the sign of the coefficient is the expected one as it can be seen in Model 3 and 4 in the table below. This could be due to the fact that, according to previous studies, fear has a shorter duration and it is more volatile than the rest of the emotions. Therefore, capturing the

[19] The time series of the valence Granger-causes purchases, since the lagged values of the independent variable provides statistically significant information about future purchases.

causal relationship between this emotion and subsequent trading activity in this case might not be possible.

Table 2: Individual behaviour: trading activity depending on past emotions *(Poisson count regression with subject fixed effects)*

	Buy_t	Buy_t		$Sell_t$	$Sell_t$
	Model 1	Model 2		Model 3	Model 4
$valence_{t-1}$	.237*	.238*	$fear_{t-1}$	2.151	2.690
$money_{t-1}$	7.29e-06	4.95e-06	$money_{t-1}$	5.79e-06	6.25e-06
$units_{t-1}$	-.021**	-.015	$units_{t-1}$	.050***	.046***
$P\ level_{t-1}$	-.00007	-.00008	$P\ level_{t-1}$	-.00012	-.00012
Buy_{t-1}	.355***		$Sell_{t-1}$	.362***	
	Prob>chi2 =0.000	Prob>chi2 =0.0586		Prob>chi2 =0.000	Prob> chi2 =0.0000
	9770 obs	9770 obs		9971 obs	9971 obs
	49 groups	49 groups		50 groups	50 groups

As a robustness check of these results, and to deep in more in the relationship between fear and sales, we run the same models to explain individual trading activity but instead of the lagged emotion variable, the current emotional response is used as independent variable. The results are displayed in table 3. We find that contemporaneous valence has no effect on how many units are bought. However, this is not the case for selling activity, where the contemporaneous fear does predict higher probability of reducing the number of assets in inventory in a given period.

Results presented in table 2 and table 3 show that those individuals with a more positive emotional state make more purchases in the next period, though there is no contemporaneous effect between these two variables. The opposite effect for fear affecting sales is found, which leads us to think that the duration and intensity of the emotion is an important factor determining how much individual´ s behaviour is affected by it. Therefore positive emotional state has a slow impact on purchases, while fear is contemporaneously correlated with sales.

Table 3: Individual behaviour: trading activity depending on current emotions *(Poisson count regression with subject fixed effects)*

	Buy $_t$	Buy $_t$		Sell $_t$	Sell $_t$
	Model 1	Model 2		Model 3	Model 4
valence $_t$	-.004	.003	fear $_t$	4.995***	4.861***
money $_{t-1}$	9.00e-06	6.50e-06	money $_{t-1}$	3.42e-06	3.87e-06
units $_{t-1}$	-.020**	-.015	units $_{t-1}$	.048***	.044***
P level $_{t-1}$	-.00011	-.00011	P level $_{t-1}$	.00012	-.00012
Buy $_{t-1}$	.355***		Sell $_{t-1}$	.363***	
	Prob>chi2=0.000	Prob>chi2 =.1950		Prob>chi2 =0.000	Prob>chi2 =0.000
	9769 obs	9769 obs		9970 obs	9970 obs
	49 groups	49 groups		50 groups	50 groups

Result 2: More neutral individuals participate less in the market

Support for result 2: In this market a trade can be conducted either by accepting an offer to sell or an offer to buy, or by submitting an offer to sell or an offer to buy which at any point in the current period can be accepted by a trader. We may consider in this case an active trader as the one who submits offers to sell and offers to buy, and a passive trader who mainly accepts these offers. Being more or less active in the market could be determined by many factors. Controlling for the overall financial position of an individual and the market prices, we look at the effect of emotions on submitting bids and asks. We run a logit model where the dependent variable is the number of bids/asks/total number of orders that a subject has made in an interval of 10 seconds.

Table 4 below shows that, at the individual level, more neutrality is associated with less initiation of orders, especially fewer bids. This seems to indicate that individuals who experience more emotions are more active in the market. Including the lagged value of the dependent variable in each model we obtain that neutrality Ganger-causes the number of bids and the total number of bids and asks that a trader submits to the market.

We now consider a further analysis in order to identify which emotions drive such behaviour. In Table 5 the same regressions are run, only in this case the lagged value of valence is used as independent variable. We find that more positive emotional state is associated with lower activity. The effect is significant for asks and total number of offers, so this suggests that the power of valence to predict purchases is driven by a tendency for individuals with more positive valence to accept asks submitted by others.

Table 4: Individual behaviour: Number of bids and asks as a function of neutrality and market variables *(logit model with subject fixed effects)*

	$bids_t$	$asks_t$	$Bids\&asks_t$
$neutrality_{t-1}$	-.247**	-.031	-.126*
$money_{t-1}$	-.00008***	.00005***	9.81e-06
$units_{t-1}$	-.058***	.054***	.020***
price $level_{t-1}$	-.0002	.0001*	-.0001
$bids_{t-1}$	.128***		
$asks_{t-1}$		.097***	
$Bids\&asks_{t-1}$			.103***
	Obs: 9770 Groups: 49 Prob>F =.000	Obs: 9971 Groups: 50 Prob>F =.000	Obs: 9971 Groups: 50 Prob>F =.000

Table 5: Individual behaviour: Number of bids and asks as a function of valence and market variables *(logit model with subject fixed effects)*

	$bids_t$	$asks_t$	$Bids\&asks_t$
$valence_{t-1}$	-.139	-.147*	-.138**
$money_{t-1}$	-.00008***	.00005***	9.77e-06
$units_{t-1}$	-.058***	.055***	.020***
price $level_{t-1}$	-.0002*	.0001	-.0001
$bids_{t-1}$	.129***		
$asks_{t-1}$		.096***	
$Bids\&asks_{t-1}$			.103***
	Obs: 9770 Groups: 49 Prob>F =.000	Obs: 9971 Groups: 50 Prob>F =.000	Obs: 9971 Groups: 50 Prob>F =.000

Result 3: Momentum traders buy more when they are in a more positive emotional state, while there is no correlation between emotions and the number of purchases and sales of fundamental value traders or rational speculator traders.

Support for result 3: Following the same criteria as in Chapter 1, we classify individuals according to their trading strategies into fundamental value traders, momentum traders and rational speculator traders. We find similar proportions of trader types as in chapter 1: 40% are fundamental value traders, 34% are momentum traders and 26% are rational speculator traders. We then analyse how emotions affect their trading behaviour. Table 6 below shows that the momentum types, who are the relatively unsophisticated traders because they buy when prices have been going up and sell when the trend has been negative, buy more based on a more positive emotional state. In previous studies it has been noted that relatively unsophisticated traders tend to accept offers made by other traders rather than submitting offers themselves (Menshikov and Plott 1998). Our results suggest that it is the momentum traders that are accepting other traders ‘offers to sell at high prices during the bubble. In order to bring some more evidence to support this result, we compute the total number of purchases relative to total number of bids for each type of trader. A higher ratio indicates that subjects are less active submitting offers to the market; that is to say, their trades are being concluded by accepting other participants´ offers. For rational speculators this ratio is 0.49, for fundamental value traders goes up to 0.60 and for momentum traders the ratio is 0.72. The ratio of sales relative to asks is not significantly different between trader types: 0.45, 0.48 and 0.42 respectively.

Table 6: Individual behaviour: trading activity depending on past emotions for different types of traders. ***(Poisson count regression with subject fixed effects)***

Buy $_t$	Fundamental Value Trader	Momentum Trader	Rational Speculator Trader
Valence $_{t-1}$	.280	.521**	-.025
Money $_{t-1}$	.00003	-.00004	-.00007**
Units $_{t-1}$	.015	-.119***	-.068***
Price level $_{t-1}$	-.0004*	.0007***	3.15e-06
Buy $_{t-1}$	.435***	.141*	.370***
	Obs: 3762 Groups: 19 Prob>F =.0000	Obs: 3396 Groups: 17 Prob>F =.0000	Obs: 2612 Groups: 13 Prob>F =.0000

Sell $_t$	Fundamental Value Trader	Momentum Trader	Rational Speculator Trader
Fear $_{t-1}$	9.018	1.219	12.796
Money $_{t-1}$	-.00005*	-.00006*	.0001***
Units $_{t-1}$	.073***	.025	.077***
Price level $_{t-1}$	.0002	-.0006**	.0001
Sell $_{t-1}$	.358***	.286***	.461***
	Obs: 3963 Groups: 20 Prob>F =.0001	Obs: 3396 Groups: 17 Prob>F =.0009	Obs: 2612 Groups: 13 Prob>F =.0000

Result 4: A better overall financial position in terms of current wealth improves traders´ emotional state

Support for result 4: A fixed effects regression in table 7 shows that a more favourable balance of cash and units improves traders' emotional state while higher price level has a negative effect on valence. We define the price level as the difference between the average price and the fundamental value of the asset at any time. Given the emotional state in period t-1, more money and units increase valence in period t, so valence is Granger-caused by these two variables.

It seems straightforward the fact that money and units are positively related to valence since they are an indicator of wealth. Since the prices are always above fundamentals over the course of the sessions, the price level variable here is actually a measure of mispricing. Our results seem to indicate that higher mispricing lowers valence perhaps because traders believe the price trajectory and thus the market value of their assets is not sustainable. Their market opportunities will then be reduced especially for those who hold many units. This is an interesting finding since our first result in this chapter is that traders with higher valence make more purchases. Therefore the emotional process underlying the formation of a bubble could be that positive emotional state enhances purchases, but as prices increase and traders find themselves in a boom, their emotions become less positive. A Spearman correlation test significant at 1% sustains that the price level variable is negatively correlated with valence (ρ= -.09).

Table 7: Individual behaviour: Emotions depending on overall financial position *(subject fixed effects)*

	Valence $_{t}$	Valence $_{t}$
money $_{t-1}$	2.51e-06*	4.01e-06**
units $_{t-1}$	.0013*	.0022***
P level $_{t-1}$	-.000044***	-.000087***
valence $_{t-1}$	.480***	
const.	-.028**	-.046***
	Obs: 9927 Groups: 50 Prob>F =.000	Obs: 9970 Groups: 50 Prob>F =.000

Result 5: Profitable purchases lead to higher valence

Support for result 5: It is also natural to think that profitable purchases or sales would improve traders´ emotional state and that bad decisions regarding trading would entail more negative emotions. We find that recent trading activity per se does not have a direct effect on emotions. This suggests that emotional state changes relatively slowly rather than quickly reacting to individual events. It also suggests that valence is primarily influenced by overall market position rather than by individual events.

Nevertheless, the more profitable a purchase is, the higher is the subsequent valence as shown by model 3 in table 8. We define the variable to measure how profitable a purchase is as the difference between the fundamental value of the asset and the transaction price.

On the other hand, how profitable a sale has been is measured by the difference between the price and the fundamental value of the asset. In this case the relationship is negative. This leads to think that it is not the profitability of the sale that affects individuals' valence, but finding himself in a high mispricing situation, which we already found to be related to negative emotional state.

Table 8: Individual behaviour: Emotions depending on recent trading activity *(subject fixed effects)*

	Valence $_t$ Model 1	Valence $_t$ Model 2	Valence $_t$ Model 3
const	-.031***	-.016***	-.005*
buy $_{t-1}$	.001	.001	.002
sell $_{t-1}$	.004	.003	.002
valence $_{t-1}$		.483***	.472***
Profit buy $_{t-1}$			.00002**
Profit sell $_{t-1}$			-.00001*
	Obs: 9970 Groups: 50 Prob>F =.6734 R2=0.0001	Obs: 9927 Groups: 50 Prob>F =.000 R2=0.355	Obs: 8990 Groups: 49 Prob>F =.000 R2=0.351

We now focus on studying the impact of emotions on market variables such as price movements and trade volume.

Result 6: Fear increases the probability of prices decreasing, while the rest of the emotions appear to help sustain bubbles

Support for result 6: We construct a dummy variable to identify the average price movement across the 15 periods. The dummy takes value 1 if p_t-p_{t-1} < 0 and 0 otherwise. We then run a logit model with subject fixed effects using the dummy variable as the dependent variable.[20] Emotions at time t-1 are the independent variables in this model. The table 9 below shows that with more fear on the part of the traders, prices in the market are more likely to decrease. On the contrary, neutrality, happiness

[20] We test fixed effects vs random effects for this model using the Hausman test (p(chi2)<0) and also the test of over identifying restrictions (p=.043) and they both reject the hypothesis that RE is consistent. Though if we compare the estimates in Table 9 as it is done by Rodriguez and Elo (2002), it seems to be the case that with random effects it is mainly the fear coefficient that significantly changes and becomes highly significant, while for some of the other coefficients the change is not as pronounced. This indicates that estimates from both specifications have some robustness. Rodriguez and Elo (2002) argue that such robustness is typically associated with the consistency of estimates.

and anger reduce the odds of this happening.[21] This seems to be in line with Lerner and Keltner (2001) findings about withdrawal emotions such as fear being associated with higher risk aversion, and approach emotions such as happiness and anger associated with risk seeking attitudes. According to this argument, it seems reasonable to think that fearful people who tend to be more risk averse would place a lower value on the asset and therefore lower prices in the market. Those who experience approach emotions give more value to the lottery the asset represents because of a risk loving attitude, leading to increasing prices.

Table 9: Market behaviour: Negative price movements depending on emotions: Comparison for logit/random/fixed effects models (dependent variable at time t)

	Logit	Random Effects	Fixed Effects
Fear $_{t-1}$	402.26	354.45**	98.08
Neutral $_{t-1}$	-5.34	-6.35**	-14.27***
Happiness $_{t-1}$	-5.03	-6.14**	-15.19***
Anger $_{t-1}$	-4.46	-5.40*	-14.30***
Disgust $_{t-1}$	-4.91	-6.17	-20.25***
Sad $_{t-1}$	-2.16	-2.96	-10.68**
constant	5.40	6.46**	

Nr. Observations RE :700

Nr. Observations FE: 546

Result 7: More between-subjects variance of emotion in the market correlates with fewer trades

Support for result 7: With regard to the trading volume in a market, it is plausible to think that there would be more trade in a period when valence is more disparate among individuals, given that positive emotional state seems to encourage purchasing and fear

[21] It is interesting to mention here that emotions in this case seem to predict price movements' direction but not magnitude. Additional analysis was done to investigate this, but emotions don't appear to have predictive power of how much prices will decrease. More precisely we constructed a variable that measured the magnitude of the price decrease as max[p_t-p_{t-1}, o] and used it as dependent variable in a regression with the lagged values of emotions as independent variables. None of the coefficients were significant.

makes traders more likely to sell. This would imply that, traders with opposite emotional profile would create thicker markets.

For each of the 15 periods, we calculate the average valence of all traders in the market and the dispersion of the valence across subjects.[22] Controlling for the average emotional state, the regression in table 10 reveals that higher variance of the valence is correlated with fewer trades in each period. This is the opposite of our hypothesis 7 and it seems to occur mainly because there are fewer bids when there is larger dispersion of valence. We have seen already that valence is negative on average across subjects. This makes us think that when there is a high dispersion of valence between subjects it is due to very negative emotional profiles and more neutral types of traders rather than positive ones in the market. Therefore in a group with high dispersion of valence, neutral subjects would be passive reflecting that in a lower number of bids and this would create fewer trades. On the other hand, less dispersion of valence in a group would mean that there are more individuals in a negative emotional state present than in the previous situations, and as we already pointed out, stronger emotions are, in general, related to more trade.

Table 10: Market behaviour: Total number of trades, bids and asks in the market depending on the variance of the valence.

	Total number of trades	Total number of bids	Total number of asks
Constant	22.62***	47.74***	44.95***
Average Valence	-71.13***	57.63	-50.19
Variance of Valence	-209.13***	-591.07***	-58.66
	R^2=0.114	R^2=0.313	R^2=0.008

Nr. Observations: 75

[22] A more detailed and in-depth analysis of the trading activity as a function of the emotional state could also control for the within period variance of the valence for each subject. This would add a new dimension to the model though would also lead to a more challenges in interpreting the results. On the other hand, it seems straightforward that individuals' resource constrains would also affect their trading activity, as it has already been shown in table 4. However, this market level analysis is intended to relate the aggregate number of trades in a period with the emotional heterogeneity across subjects in a market, whereas their particular resource constrains continuously change during the period as they trade.

5. Conclusions

In the previous chapter we found a number of patterns that conform to the general intuition expected about the connection between emotions and asset prices. Based on these findings, in this chapter we go one step further in the analysis of these links. The purpose is to explain the underlying interaction process that takes place when emotions affect decisions in the market and these have influence over one's financial position, which in turn has an emotional impact on traders.

We use tick-by-tick data to establish causal relationships between emotions and individual behaviour, and a 15 period dataset to investigate how emotions affect market level variables. We find that, at the individual level, positive emotional state causes more purchases and fear is related to more sales. Subjects who are more neutral participate less in the market submitting less bids and asks. Also there seems to be a different effect of emotions if we consider different types of traders separately. In this sense we show that momentum traders are influenced by a positive emotional state and buy more, while fundamental value traders or rational speculators don't seem to base their decisions on emotions.

In addition, a better overall financial position has a positive effect on emotions as well as a profitable purchase. Recent trading activity itself, as a purchase or a sale, does not provoke significant emotional responses.

At the market level we find support for fear predicting prices decrease in the next period, and emotions like happiness and anger helping sustaining a bubble. Also in aggregate terms, we find that with more disparate valence among traders and a more negative average emotional state, fewer trades take place.

In light of the results obtained with this micro-level analysis we can infer about the emotional process that, to some extent, influences the creation and magnitude of such puzzling phenomena as bubbles and crashes in asset markets. Thus, it could be argued that more positive emotional state enhances purchases and therefore overpricing, especially when there are momentum traders in the market whose actions seem to be driven by valence. Also more emotions in general create more activity in a market, in particular more bids. These facts contribute to the creation of bubbles which are sustained by approach emotions and less risk averse attitudes related to them. Generally the larger the bubble is, the lower becomes the valence, and this could be due to the fact that subjects realize that prices and therefore the value of their assets are not sustainable. As fear appears in the market, a crash becomes more likely to occur.

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Chapter4.

When do structured funds become too good to be true? An experiment

1. Introduction

Structured products make up a significant part of most developed countries' financial systems. According to the SPA (Structured Products Association) over 180 billion $ were invested in the European fund market in 2005, 70 billion $ in the United States and almost 50 billion $ in the Asian market. In the last years market trends have changed little despite the Great Recession. In 2012, according to the Financial Times, the sales of structured products continued on the rise despite warnings of the financial regulators about their risks and complexity.

Parallel to the growth of structured products in particular, the growth of the mutual funds industry over the recent decades highlights the ability of these funds to channel investors' money into the financial markets. Khorana and Servaes (2012) report that assets in the mutual fund industry increased by a factor of 200 in the period 1976-2009. Moreover, about 45% of the households in the U.S. invest in them, according to ICI (2010). Investment in mutual funds is then a widespread activity which also non-specialized agents undertake. In fact, many citizens invest in guaranteed mutual funds under the form of retirement plans.

The significant role of mutual funds in most markets has aroused both social and academic interest. Within this context, the aim of the present study is to analyze the individual demand for structured mutual funds according to varying levels of the difference in expected return when compared to a bond, and under different information conditions.

The demand for mutual funds has been extensively analyzed in the literature concerned with evaluating fund efficiency. An example of research on structured products demand is Breuer et al. (2007) who successfully explain demand for two of them using a modified hedonic framing rule. Behavioral biases have already been found in experimental studies focusing on mutual funds. Annaert *et al.* (2005) carried out an experiment on framing in capital guaranteed funds and observed that investors tend to choose in a different way when they are aware of some characteristics of the probability distribution of the potential gains/losses. Barreda-Tarrazona *et al.* (2011) experimentally analyzed the importance of providing accurate information about the socially responsible character of a mutual fund in order to help investors express their ethical preferences.

Kliger *et al.* (2003) also opted for an experimental approach to uncover inconsistency with standard Expected Utility Theory in mutual fund investor behavior: investors' tendency to delegate money to a fund increases with performance, even when performance is uninformative. Choi *et al.* (2010) designed an experiment to study the "law of one price" in fund investment. They presented the subjects with a menu of four funds with the same fundamentals but charged higher fees for the funds presenting higher past performances (due to the different launching dates). The authors found that people heavily relied on the annualized past return of funds in making fund selection decisions, even ignoring the fees in many cases. Similar results were obtained by Anufriev *et al.* (2012) in an experiment in mutual fund choice, but in their case, centered on the role of past information and fee structure. They observed that fund choice decision is heavily driven by past return, even when this information is irrelevant. A very similar bias to this one is also obtained in our experiment for the role of information about alternative scenarios.

The above-mentioned literature analyzes investor behavior and demand for mutual funds and in most cases unpredicted behavior appears, to a great extent related to the information available to the investors or to the framing of that information. These articles add to a growing body of evidence that individual investors make suboptimal asset allocation decisions. The present study proposes a simple experimental design, which allows for an analysis of individual investor behavior in structured mutual funds according to variables such as expected return and risk (we vary the former while we keep the latter constant), and, at the same time, tries to eliminate possible behavioral biases such as past performance effect, disclosure of the probability distribution of the potential gains/losses effect, or other features that might difficult comparisons: fees, non-portfolio services, etc. This approach also allows us to evaluate the effect that the structure of the available information has on investor behavior and, consequently, on the demand for the funds.

The study was undertaken in the Laboratory for Experimental Economics (LEE) at the Universitat Jaume I where a sample of university students made investment decisions according to different expected return and information conditions. They had to invest a fixed amount either in a bond or in a structured product, which secured part of the invested capital and yielded additional benefits if the (simulated) stock market experienced a positive evolution. Our results show that information available to investors, and particularly the order in which it is presented, generates significant biases in their decision making that can have both positive and negative effects on their behavior.

The chapter is organized as follows: in the next section we outline the design of the experiment. In the third section we present our hypotheses. Then, we analyze the results obtained in the experiment. After that, the main conclusions drawn are presented.

2. The experiment

2.1. Participants

A total of 607 undergraduate students from different majors, mainly business administration, engineering and economics, participated in the between-subjects study: 287 in Treatment 1, 227 in Treatment 2 and 93 in Treatment 3. Subjects were recruited using the Orsee System (Greiner, 2004) and none of them participated in more than one session. Our experiment consisted of 60 scenarios with the agents having to choose between two investment options in each of them: a risk free asset (a bond) and a structured mutual fund. Each of the 60 scenarios presented a particular combination of the interest rate of the bond on one hand, and the secured and expected additional benefits of the fund, on the other hand.

The experiments were programmed in PHP and Java and carried out in the Laboratory for Experimental Economics (LEE) at Universitat Jaume I in Castellón, Spain. In order to give a real value to each of the decisions made using experimental units (EU), the equivalence of 1 € = 8,000 EU was introduced. Average earnings were 163,962 EU (20.5 €) per participant in about one and a half hour.

2.2. Experimental design and framework

The experiment consists of three parts. The first part is the most central to this research: subjects make investment decisions in each one of the 60 scenarios. The second part of the experiment is a risk aversion test using a lottery task. And finally, in the last part of the experiment, subjects fill out a personal questionnaire.[23]

For the first part of the experiment, subjects were given specific instructions about their tasks, which were also read to them aloud by the experimentalist. The experiment was then run for each subject on an individual computer. A screen appeared for each scenario and the investor had to choose where to invest her total endowment of 100,000 EU between two investment alternatives, "A" or "B".[24]

The investment alternative "A" was a fixed return risk-free bond. Equation [1] describes the final value of the investment after *n* periods ($V_{n,j}$) for the *j* scenario as the result of reinvesting the initial V_0 up to *n* yearly periods, given a simple r_j capitalization. In the experiment setting, for each scenario, *n* is equal to 3 years and V_0 is 100,000 EU. In Treatment 1, for scenarios going from 1 to 30, this investment yields a 3% annual interest which implies within 3 years a 9% appreciation. In order to simplify to the maximum the investor's calculations, the yields were calculated with a simple capitalization. Starting with the scenario number 31 up to the 60th, the bond yields a 7% yearly which implies a 21% r_j in three years (see Table 1).

$$V_{n,j}^{A} = V_0\left(1+r_j\right) \qquad [1]$$

On the other hand, the alternative "B" was to invest in a structured mutual fund. At the end of a three year period this investment fund has a final value as the expression [2] shows. The first component represents a guaranteed part of the investment ($1+g_j$) which varies from -3% to 12% depending on the scenario. Technically speaking, it is when this percentage is positive that we can actually consider the fund a guaranteed mutual fund. The second component yields an extra value depending on the positive evolution of an index representing the stock market. In each of the scenarios, subjects are offered a particular percentage (ρ_j) over the appreciation of the stock market (r_m).

[23] The experimental instructions and the questionnaire are available upon request to the authors.
[24] Note that the investors could not divide their endowment, they had to invest it fully in one of the two options presented to them.

As equation [2] shows, this component is asymmetric, given that it yields an additional benefit in case the stock market appreciates, but does not entail losses when the stock indicator does not have a good performance. This asymmetry is typical of the options.[25]

$$V_{n,j}^{B} = V_0(1 + g_j) + V_0 \cdot \max(0, \rho_j \cdot r_m) \qquad [2]$$

In Treatment 1, every five scenarios the value of the upside participation ρ_j is successively: 10, 30, 60, 100 and 110 percent. This structure is repeated twelve times throughout the whole session. Table 1 summarizes the values of g_j and ρ_j parameters in each scenario for the fund investment "B" as well as r_j for the bond investment "A". Please note that the particular order of the scenarios presented in Table 1 was used in Treatments 1 and 3, while in Treatment 2 the exact same scenarios were presented in different random orders to each of the subjects.

[25] Actually, the mutual guaranteed funds are products normally structured by means of investment in bonds which at the due date provide the invested capital security, and the payment of an option premium which is bounded to a certain stock market evolution gives us the second component. Holmen et al. (2012) experimentally study how option-like incentives in asset markets can induce higher prices and more risk taking by agents.

Table 1

Along the 60 scenarios, the table reports the values of the 3-year return (r_j) in [1] for the A investment. For the B investment, we report the values of the 3-year return of the guaranteed part, (g_j) in [2], and the upside participation on the stock market 3-year return of the option part, (ρ_j) in [2].

	Alternative A (Risk-free bond)	Alternative B (Structured mutual fund)			Alternative A (Risk-free bond)	Alternative B (Structured mutual fund)	
Scenario	Guaranteed 3-year return(r_j)	Guaranteed 3-year return (g_j)	Percentage over the (+) stock market 3-year return (ρ_j)	*Scenario*	Guaranteed 3-year return(r_j)	Guaranteed 3-year return (g_j)	Percentage over the (+) stock market 3-year return (ρ_j)
1	9%	-3%	10%	*31*	21%	-3%	10%
2	9%	-3%	30%	*32*	21%	-3%	30%
3	9%	-3%	60%	*33*	21%	-3%	60%
4	9%	-3%	100%	*34*	21%	-3%	100%
5	9%	-3%	110%	*35*	21%	-3%	110%
6	9%	-1.5%	10%	*36*	21%	-1.5%	10%
7	9%	-1.5%	30%	*37*	21%	-1.5%	30%
8	9%	-1.5%	60%	*38*	21%	-1.5%	60%
9	9%	-1.5%	100%	*39*	21%	-1.5%	100%
10	9%	-1.5%	110%	*40*	21%	-1.5%	110%
11	9%	0%	10%	*41*	21%	0%	10%
12	9%	0%	30%	*42*	21%	0%	30%
13	9%	0%	60%	*43*	21%	0%	60%
14	9%	0%	100%	*44*	21%	0%	100%
15	9%	0%	110%	*45*	21%	0%	110%
16	9%	3%	10%	*46*	21%	6%	10%
17	9%	3%	30%	*47*	21%	6%	30%
18	9%	3%	60%	*48*	21%	6%	60%
19	9%	3%	100%	*49*	21%	6%	100%
20	9%	3%	110%	*50*	21%	6%	110%
21	9%	6%	10%	*51*	21%	8%	10%
22	9%	6%	30%	*52*	21%	8%	30%
23	9%	6%	60%	*53*	21%	8%	60%
24	9%	6%	100%	*54*	21%	8%	100%
25	9%	6%	110%	*55*	21%	8%	110%
26	9%	7.5%	10%	*56*	21%	12%	10%
27	9%	7.5%	30%	*57*	21%	12%	30%
28	9%	7.5%	60%	*58*	21%	12%	60%
29	9%	7.5%	100%	*59*	21%	12%	100%
30	9%	7.5%	110%	*60*	21%	12%	110%

As in real financial markets, the value of the stock market evolution r_m is not known. For this experiment we considered it a random variable with a normal distribution (for treatments 1 and 2). Even though any simulated data could have been used, we have taken the annualized standard deviation of the Ibex 35 daily return over the three year period 2008-2010 and the annualized mean of the daily return over the past 10 years. As this mean is positive, the probability of a positive r_m is higher than that of a negative value, which is something expected from the equity risk premium hypothesis.

Subjects were informed about investment in stock markets being a risky investment. They were also informed that in the simulated stock market there was a 60% probability for the revaluation to be positive and a 40% probability for it to be negative. And the standard deviation and a table summarizing the distribution of r_m were reported in the instructions for Treatments 1 and 2. These values were generated, as we explained above, using a normal distribution for the 3-year return with 12.021% mean and 46.8% standard deviation parameters. In Treatment 3, in order to determine the stock market revaluation, we replaced the computer generated value taken from the normal distribution of r_m with a simple human made die roll. In particular, a volunteer subject casted a 10 sided die offering an equivalent 40% probability of negative revaluation and an equal 12% mean expected revaluation to that of the normal.

After the 60 scenarios were run and all subjects made their choices, the program randomly provided a value for r_m (in treatments 1 and 2) drawn from the aforementioned normal distribution and converted to 0 in case it was negative. In treatment 3 a ten-sided die casted by a volunteer participant determined the stock market revaluation after all participants had made their decisions and it was also converted to 0 in case it was negative. Immediately afterwards, another participant volunteered to cast the dice in order to randomly obtain a value j' from 1 to 60 which selected the scenario that would be paid out in cash in that session[26]. Finally, subjects who had decided to invest in option A in the selected scenario received the amount corresponding to equation [1] and for those who had chosen investment B, their earnings were determined by equation [2] according to the realized value of r_m and the parameters g_j and ρ_j for the selected scenario j'.

[26] Two dice were used. One with six faces (1-6) determined the first digit and one with 10 faces (0 to 9) determined the second digit. Note that the 6 in the first dice could mean either 0 when accompanied with any value greater than 0 in the second die, or 6 when the second die showed a 0.

We ran 9 sessions of Treatment 1 in which the scenarios were sequentially presented as shown in Table 1(with increasing expected returns for the fund). In Treatment 2, the exact same 60 scenarios (combinations of fixed and additional potential benefits of the two investment options) were presented in random order, independent for each subject, to a new pool of subjects. We ran 5 sessions of Treatment 2. Two other sessions were ran under Treatment 3 conditions with the rolling die mechanism for determining the stock market revaluation and the same 60 scenarios sequentially presented as in Treatment 1.

We had three main goals: (1) to observe any changes in the way the capital endowment was invested between the risky and the risk free assets when the expected return varied. (2) to see if the ordering in which the investment scenarios were presented to the participants made a difference in their investment decisions by comparing treatments 1 and 2. And finally, (3) to study whether more transparent information about the return generation process would influence decision making by comparing treatments 1 and 3.

In the second part of the experiment, we used a lottery to assess the subjects' risk aversion very similar to the one used by Alfarano *et al.* (2006). This is a modification of a Holt and Laury (2002) lottery test where one of the options is not probabilistic and increases sequentially in its fixed value and the other is probabilistic but its expected value remains fixed. In this part of the experiment eleven lottery choices are displayed. The risky option, which remains available along the eleven scenarios, is to obtain 48,000 EU or zero EU with 50% probability. The safe option consists of a secure payment which ranges from 4,000 UE in the first scenario, to 31,000 UE in the last one. After all choices are made, one of the eleven scenarios is randomly chosen[27] and also the 50% probability situation is solved by a volunteer tossing a coin. Then the payment to each participant in the risky lottery is determined according to these events. An expected rational behavior would be to choose the risky option in the first scenarios when the riskless offer is low and afterwards, with higher secured yields, switch to the safe option at some point of the decisions chain.[28]

Finally, the third part of the experiment consisted of a questionnaire with demographic and idiosyncratic data. The first three questions were meant to reveal the financial knowledge level of the participant. The following four questions evaluated how important investment yields and risks were for the subject and whether they had

[27] This was done by a volunteer participant throwing a 12-sided die. If 12 came up she had to cast the die again.
[28] The analysis of the data obtained from the risk aversion test is available upon request from the authors.

any asymmetric perception in the evaluation of gains and losses. The last four questions aimed at evaluating subject's rationality when selecting investments.[29]

3. Hypotheses

In the mean-variance framework of choice among financial assets, for a given level of risk, an asset offering a higher expected return would always be preferred over one with a lower expected performance. In our design, the only risk faced by the participants concerns the future evolution of the (computer or human generated, depending on the treatment) simulated stock market revaluation r_m, on which the variable part of the structured fund return is based. In this way the underlying risk is kept constant for all the guaranteed products within a given treatment. On the other hand, the alternative investment possibility is a risk-free bond. In this setting, the binary decision of choosing between the two investments should be made in terms of the subjectively estimated expected utility of each alternative according to each individual's level of risk aversion. When one of the investment alternatives unequivocally increases its expected return with respect to the other without varying its risk, it should be more preferred by our investors. This can be expressed as appears in our Hypothesis 1:

H.1 Investment in the structured fund is increasing in the difference between the expected return of the structured fund and that of the risk free bond.

We understand that each investor may subjectively attach different utility to the same level of expected return. This is due to the fact that not every person is risk-neutral. Indeed the experimental literature there is ample evidence that people tend to be risk-averse even for the relatively small amounts of money they can gain in experiments. As the only risk in our experimental design concerns the structured fund, this will be in general the least preferred option for the more risk-averse investors, and vice-versa:

H.2 Risk-averse (loving) participants will invest more in the bond (structured fund).

[29] The responses obtained from the questionnaire were not significant in the econometric analysis.

We think that this effect could be so important as to totally nullify the effect of big expected return differentials between the investment options, but only for the extremely risk-averse or extremely risk-loving individuals. We introduce expected return differences up to 30% in the design, which are very big for regular investment standards. Besides, we do not expect many subjects to show an extreme degree of risk aversion or lovingness. Under these circumstances, the aggregate effect of these few subjects' decisions will in any case be very small.

H.3 Extremely risk averse participants will not invest in the structured fund even for high differences in the expected returns.

According to Miller (1956) "Everybody knows that there is a finite span of immediate memory and that for a lot of different kinds of test materials this span is about seven items in length… and there is a span of absolute judgment that can distinguish about 7 categories." That is, the ability of people to keep in mind and compare a large set of options is limited. In our case we presented each subject with 60 binary choices. In Treatment 1 the information was presented sequentially, in cycles with increasing order of expected returns, so that it was easy for the subjects to categorize and compare the different assets across the scenarios. According to the psychological research on the matter, in Treatment 1 and 3, subjects should be able to recall and easily compare at least within each group of 5 scenarios with stable fixed returns for both investments and increasing index-performance related expected returns. However, in Treatment 2, the sequence of scenarios did not follow any logic and what was "stored in memory" was a juxtaposition of a steadily increasing number of offers with different expected values.

Malhotra (1982) found that respondents experienced information overload when they were presented with 10, 15, 20 or 25 choice alternatives. If the independence of irrelevant alternatives held in our case this would not pose any problem, because all 60 binary choices are independent in our design, in the sense that only one of the scenarios was to be selected in the end, and all other 59 choices would be totally irrelevant for determining the payment to the particular subject. No matter how attractive or unattractive an investment seen in prior scenarios was, that should not have any weight in the binary decision being presented in a particular alternative scenario. However, if the subject tried to keep in mind all the investment options that were presented to her in order to carry out a global comparison, she would soon be confronted to her memory and judgment limits.

H.4 The order in which information is presented to our participants (sequential vs. random) will generate biases in their decisions related to information processing limitations: i) a sequential presentation of better alternatives can introduce return chasing, as has been previously observed in the literature, but, on the other hand, and thanks to our design, ii) it can make the extremely generous offers seem "too good to be true" and thus less chosen.

Our argument is that the memory and judgment limitations, operating when the investment options are presented randomly (T2), are greatly reduced when these are sequentially ordered in groups of five choices in which the only difference is the increase in the upside market participation (T1 and T3). This increase may make the guaranteed option become more attractive in comparison to the bond than what the difference in expected returns would justify. However, when the upside market participation (which increases from 10% up to 110%) goes above 100% it could appear to be "too good to be true", i.e. the guaranteed investment may seem to be offering too much. In this case, subjects could come to doubt the likelihood of a positive stock market return stated in the instructions.[30]

In order to alleviate this possible fear of some participants, that high stock market revaluations could be less likely to be selected by the computer than they should, in the third treatment we have replaced the black box draw of the normal distribution generated by the computer with a volunteer participant casting a 10 sided die offering an equivalent 40% probability of negative revaluation and an equal 12% mean expected revaluation to that of the normal. All other characteristics of the treatment are as in T1. What we expect is that the more transparent random generation process used in T3 makes high upside participation investments to be perceived as credible as small upside participation ones.

H.5 Higher transparency in the random generation process followed for obtaining the market revaluation (human die roll vs. computer draw) will alleviate the bias of not choosing options offering high upside participations.

[30] In fact, for a high guarantee, a real firm which could sell this particular fund would lose money in case of a positive revalorization of the stock exchange.

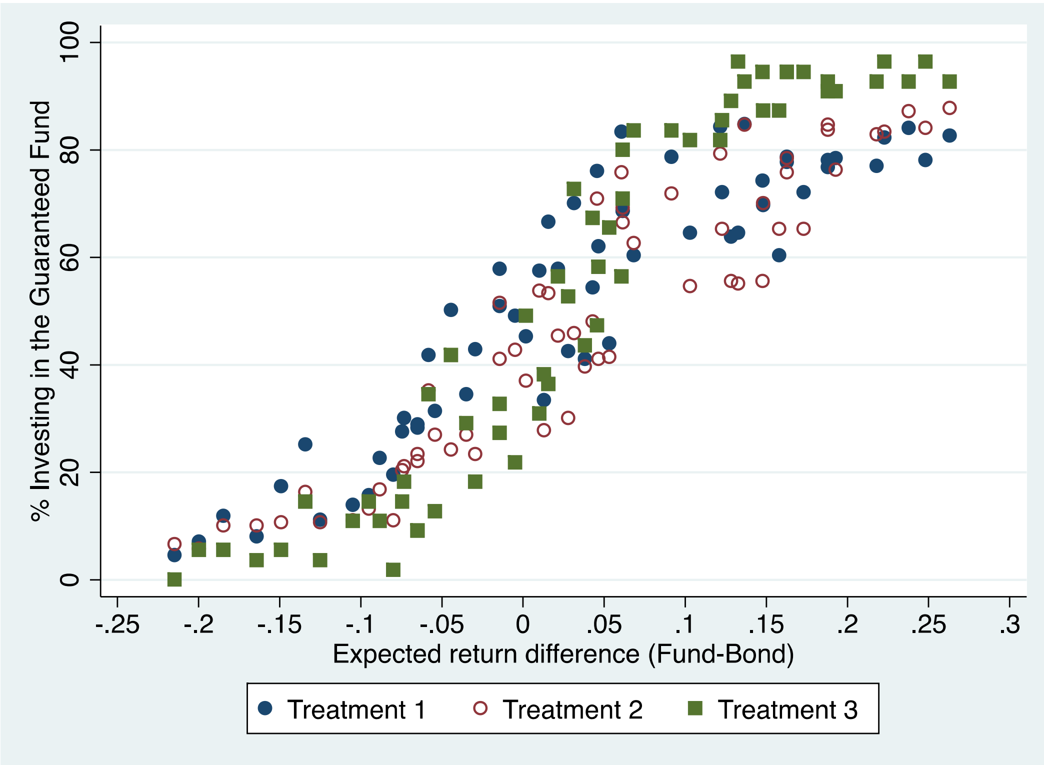
4. Results

4.1 Aggregate results on guaranteed mutual funds investment.

Figure 1 offers us some graphical evidence for hypotheses 1 and 2. It allows us to infer from the subject's choices that a very reduced number of people are highly risk loving or highly risk averse and they stick to their preferred option: the risky or the safe one respectively, both in the presence of highly positive or highly negative return differentials between the fund and the bond. In fact there are probably more extremely risk averse subjects than extremely risk lovers (around 9% and 1% respectively). However, most investors (approximately 90%) change their decision in the hypothesized way alongside the evolution of the difference in expected returns between the two assets following a sigmoid logistic shape.

Figure 1

Percentage of investors choosing the structured fund according to its expected return difference with the bond.



Comparing treatments 1 and 2 in Figure 1 we can observe that in Treatment 1, when the scenarios are easier to compare (because they were presented in the sequential order shown in Table 1), the percentage of people investing in the guaranteed fund is greater for most expected return differentials (full dots are normally placed higher than hollow dots). So, investors have a higher preference for the fund when they can easily compare the independent scenarios and observe that the fund offers increasingly higher expected gains, while the bonds' remain constant. This is the first casual evidence of our Hypothesis 4.i. As for treatment 3, it appears that a more transparent way to generate the stock market revaluation consistently results in less investment in the mutual fund when the expected return difference is negative and more investment when it is positive than in the other two treatments.

This observation supports the idea that investors may suffer from a kind of "past returns" or "trend" illusion, similar to Chartism, due to which they tend to believe that a good history is in some way guarantee of a good future performance, even in totally independent realizations as those presented in our experiment. This result is complementary to the ones recently obtained by Choi *et al.* (2010) and Anufriev *et al.* (2012), even though our situation is not identical, given that the offers that we present to the investors correspond to alternative worlds that might be realized in the end or not, and not to real past performance.

This "trend" effect can also be observed numerically in Table 2a. In order to statistically support our graphical observations above, we have conducted a battery of Kolmogorov-Smirnov tests between the distributions of subject's proportions of structured fund choice for different groups of scenarios and we have obtained statistically significant evidence that T1 distribution stochastically dominates T2's for the whole sample and for the two 30 scenarios subsamples.[31] However T3 stochastically dominates T1, but only for the last 30 scenarios when the fund is relatively less attractive. This indicates that with a more transparent random generation process subjects decide more in accordance to the expected return difference. The observed pattern shows some evidence in favor of our Hypothesis 5, given that when the attractiveness of the fund is greater more participants trust to invest in the fund for T3 than for T1.

[31] Only when we further break down the sample into the 12 cycles of 5 periods we obtain that the difference is significant in half of the cycles, very precisely matching what appears in Figure 2.

Table 2a

Proportion of investors that chose the structured fund for different groups of scenarios.

	All	Half	(I)	(II)	(III)	(IV)	(V)	(VI)
Scenarios:	1-60	1-30	1-5	6-10	11-15	16-20	21-25	26-30
T1 Average	52.39%	64.64%	52.12%	54.14%	62.22%	67.03%	73.93%	78.39%
T2 Average	47.23%	58.82%	40.70%	39.20%	60.96%	62.20%	72.07%	77.79%
T3 Average	53.78%	65.12%	60.86%	53.73%	63.44%	67.52%	70.10%	75.05%
K-S p-value T1 vs. T2	**0.000**	**0.000**	**0.000**	**0.000**	0.846	0.155	0.315	0.400
K-S p-value T1 vs. T3	0.253	0.094	**0.007**	**0.042**	0.284	0.237	0.056	0.096
Scenarios:		31-60	31-35	36-40	41-45	46-50	51-55	56-60
T1 Average		40.13%	21.95%	28.15%	38.67%	42.43%	48.98%	60.62%
T2 Average		35.65%	20.17%	21.76%	34.44%	35.59%	43.70%	58.23%
T3 Average		42.43%	23.44%	30.10%	42.15%	48.60%	50.10%	60.21%
K-S p-value T1 vs. T2		**0.003**	0.632	**0.060**	0.449	**0.020**	**0.028**	0.542
K-S p-value T1 vs. T3		**0.019**	0.187	0.126	0.136	**0.048**	0.504	0.633

Table 2b

Median number of scenarios in which agents chose the structured fund and Mann-Whitney test between treatments

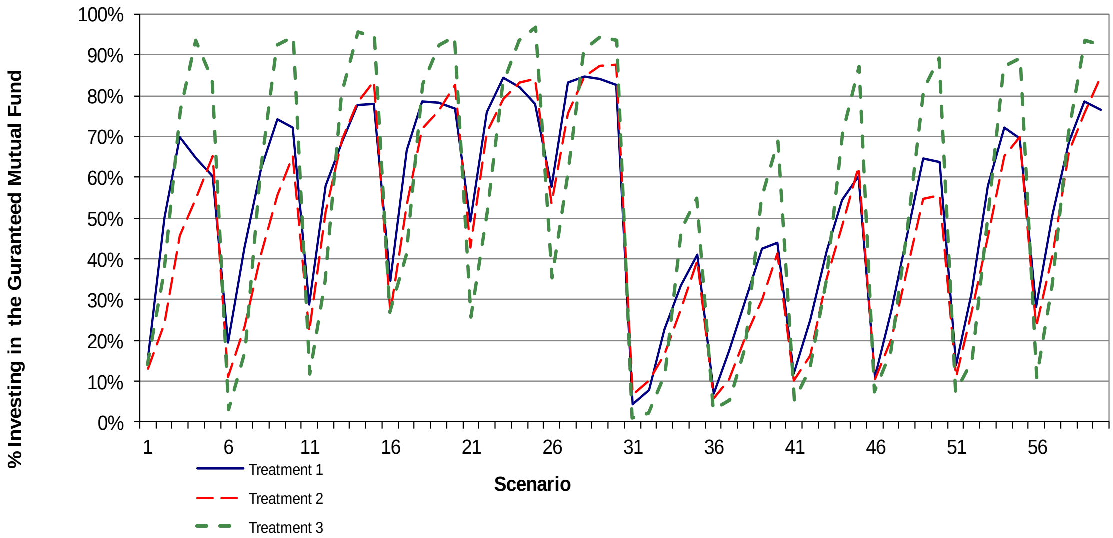
Scenarios:	All	Half	(I)	(II)	(III)	(IV)	(V)	(VI)
	1-60	**1-30**	1-5	6-10	11-15	16-20	21-25	26-30
T1 Median (287 obs)	33	20	3	3	3	4	4	4
T2 Median (227 obs)	28	18	2	2	3	3	4	4
T3 Median (93 obs)	33	19	3	3	3	3	4	4
Mann-Whitney p-value	**0.0002**	**0.0001**	**0.0000**	**0.0000**	0.4801	**0.0207**	0.1591	0.2811
Mann-Whitney p-value	0.5608	0.4707	**0.0393**	0.4733	0.7787	0.5890	**0.0403**	**0.0451**
	Scenarios:	**31-60**	31-35	36-40	41-45	46-50	51-55	56-60
T1 Median (287 obs)		12	1	1	2	2	3	3
T2 Median (227 obs)		10	1	1	2	2	2	3
T3 Median (93 obs)		13	1	2	2	2	3	3
Mann-Whitney p-value		**0.0231**	0.7286	**0.0209**	0.0944	**0.0021**	**0.0134**	0.2815
Mann-Whitney p-value		0.2378	0.1973	0.2768	0.2687	**0.0693**	0.9978	0.6198

In Table 2b we compare the median number of scenarios in which subjects invested in the structured fund (instead of the whole distribution of the proportions of investors), obtaining robust results supporting the statistical significance of a positive difference in median investment in the guaranteed fund in T1 with respect to T3. The median number of scenarios in which subjects selected the guaranteed fund is 33 out of 60 in T1, while only in 28 out of 60 in T2. In fact, performing an additional Mann-Whitney test we obtain that the probability for a random scenario that a randomly chosen agent from T1 has selected the guaranteed fund more often than a randomly chosen agent from T2 is 60%. *The tests above offer evidence consistent with our Hypothesis 4.i, confirming the existence of a "trend" effect.* We observe no significant differences regarding the "trend" effect between T1 and T3, as expected.

If we analyze Figure 2, which describes the evolution along the scenarios of the percentage of investment in the structured fund, behavioral paths can be identified.

Figure 2

Guaranteed mutual fund investment along the 60 scenarios of the experiment by treatments



The guaranteed return of the mutual fund is -3% in the first group of 5 periods, while the bond ensures a 9% return on the investment for the same time horizon. In the first period, with an additional 10% yield over the stock market revaluation for the mutual fund, only 18% of the participants prefer the risky option, which seems to indicate that a maximum 12% loss is compensated for them by a highly positive expectation on the evolution of the stock market. In Treatment 1, within this first group of five scenarios there is a maximum investment in the Fund option in the third scenario where a 78.9% of participants decide that a 12% maximum loss is compensated by a 60% upside participation. In the subsequent 4th and 5th scenario we observe a fall in the mutual fund investment: 77.5% and 71.8% of investors decide to invest in the fund for a ρ_j value of 100% and 110% respectively. This pattern is not infrequent in Treatment 1: in the second group of five scenarios a similar phenomenon is also observed, that is, mutual fund investment rises from 21.1% in the first scenario up to 85% in the 4th scenario where it reaches the maximum and finally in the fifth scenario, when the ρ_j value goes beyond 100%, investment in the fund drops to 79%. This extreme concavity feature is repeated throughout the whole of Treatment 1, especially in the scenarios 1 to 30 where the difference between the guaranteed three years return of the bond and the guaranteed part of the mutual fund is narrower than it is for the last 30.

This is in our opinion the most original result of this experiment. While one would expect a monotonic increase in investment in each 5 scenarios cycle together with the increase in the upside participation, we observe that for percentages higher than 100% investment in the structured product in fact nearly always decreases in Treatment 1. We call this finding the “too good to be true” effect, which has some implications for the advertisement of structured products. Offering such high upside participations could in effect be conveying to the risk averse investor the idea that the event of the stock market actually revaluating is highly unlikely, because otherwise such great upside participation would not be offered. In our experimental case, students may doubt whether in the scenarios where the offer is so high the actual probability of a positive revaluation really is 60% as stated in the instructions.

However still in Figure 2, we can also observe that the “too good to be true” effect totally disappears as soon as the subjects are no longer able to easily compare all the possible investments. In T2, just more of them invest in the fund when the upside participation is 110% than 100%. Seeing all the binary options in random order seems not to make them behave more cautiously for extremely high offers. Also introducing a more transparent way of generating the stock market revaluation in T3 dramatically reduces the “too good to be true effect”, as stated in our H5. Also the percentages of investment in the fund with medium to high upside participation are much bigger than in the other two treatments.

In order to provide statistical evidence for the “too good to be true” effect we have conducted a McNemar symmetry test. This test compares whether the number of times that an agent was choosing the guaranteed fund when ρ_j was 100% and he decided to switch his selection to the bond when ρ_j increased to 110% is significantly different from the opposite switch, that is, that an agent was choosing the bond when ρ_j was 100% and decided to change to the fund for 110%. Our results can be found in Table 3. For the first 30 scenarios of treatment 1 we find that significantly more times the case was that those choosing the fund switched to the bond, thus statistically supporting the “too good to be true” effect. For the last 30 scenarios of T1 there is no significant decrease in fund investment, but also no significant increase -still consistent with our hypothesized effect-, while for both the 30 first and the 30 last scenarios of T2 we observe the opposite phenomenon: that significantly more people switched from the bond to the fund when the upside market participation increased over 100%, as expected if no “too good to be true” effect applies and investors just follow the guide of the expected return difference. *These tests together support our Hypothesis 4.ii that a “too good to be true” effect arises when the relatively better and worse investment scenarios are made easier to compare.*

In T3 we obtain that there is no significant decrease in the number of participants investing in the fund when the upside participation gets very high for the first 30 scenarios and actually that there is a significant increase in the last 30 scenarios, thus confirming our Hypothesis 5 that transparency about the market revaluation random generation process alleviates the “too good to be true” effect.

Table 3

Number of observations choosing the fund for a 100% upside participation switching to the bond for 110% *versus* number of observations choosing the bond for 100% upside participation switching to the fund for 110%

Scenarios:	1st Half	2nd Half
	1-30	**31-60**
T1 (1722 obs)	142 vs. 105	110 vs. 138
McNemar p-value	**(-) 0.0218**	(=) 0.0862
T2 (1362 obs)	121 vs. 196	138 vs. 257
McNemar p-value	**(+) 0.0000**	**(+) 0.0000**
T3 (55 obs)	23 vs. 28	20 vs. 54
McNemar p-value	(=) 0.5758	**(+) 0.0001**

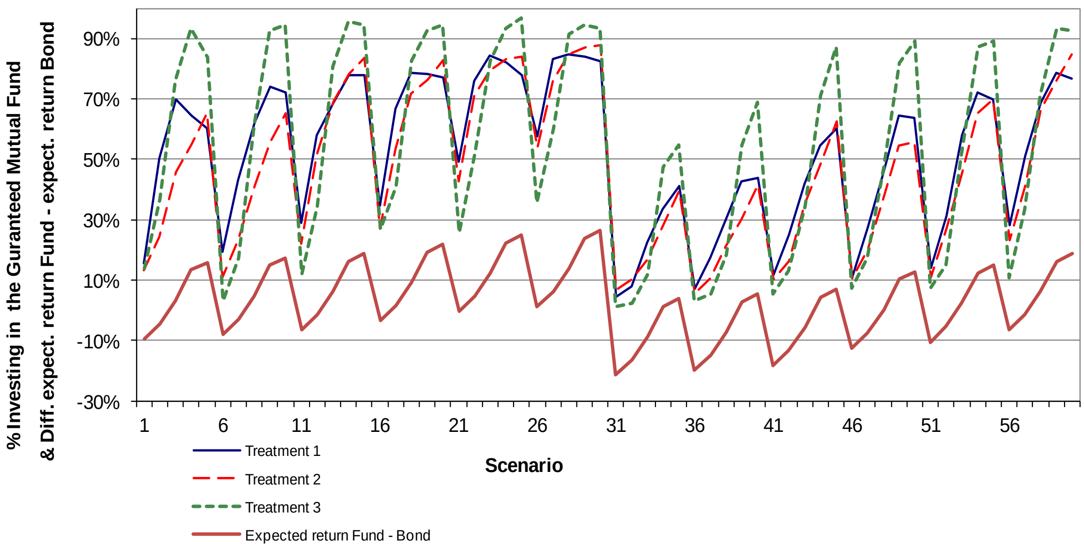
+/- Stands for an increase/decrease in the relative fund purchases when the upside market participation increases from 100% to 110%

That is, in T2, when subjects see the 100% and 110% upside participations in random order mixed with the other lower ones (without observing the sequential increase in each 5 scenario group) they do not infer any negative signal in such attractive offers. Thus, spotting "nearly incredible" offers becomes harder when comparing offers becomes cognitively harder. This fact has implications for financial regulatory authorities. Clearly organizing and categorizing existing investment opportunities could help investors in discriminating reasonable offers from highly unlikely to be fulfilled ones. Also exposing dark spots in the information about how the returns are generated can help the investor to trust less a given offer (e.g. a Ponzi scheme).

Figure 3 shows the expected return differences between the fund and the bond for each scenario. In this way they can be used as a benchmark for rational risk neutral decision makers. As our participants varied in their degree of risk-aversion we never observe that all investors follow the clear-cut risk neutral prediction. However, we do observe that the percentage of investors choosing the fund approximately follows the difference between the expected return of the fund and the bond, as proposed by Hypothesis 1. This link is clearly broken only for Treatment 1, in the scenarios where we observe the "too good to be true" effect.

Figure 3

Difference in expected returns between the guaranteed fund and the bond for each scenario against the evolution of the percentage of investors choosing the fund in all treatments.



4.2 Econometric analysis.

In this section we further analyze the statistical significance of our results using panel regression methodology. In order to obtain a more precise measure of the impact of the guarantee and the stock market upside participation on the demand for the mutual fund investment we construct a model using as independent variables those appearing in equations [1] and [2]: the guaranteed return of the bond (r_j), the guaranteed return of the structured fund (g_j), and the upside participation offered by the fund (ρ_j). We have also introduced in the analysis the individual level of risk aversion estimated from our lottery tests (the higher the value the less risk aversion a subject showed in the test). Besides, we also employ as a variable the squared term of the upside participation ($\rho_j^{\,2}$) with the aim of capturing, when this quadratic effect is significant, the concavity of the demand of the mutual fund. This concavity must be big for the "too good to be true" effect to be significant.

The obtained data form a panel with 607 individual decisions across 60 periods (287 in Treatment 1, 227 in Treatment 2 and 93 in Treatment 3). Given that we identified around 10% investors with non robust answers to the risk aversion test, the respective observations were eliminated from our analysis and we remained with a still relatively large sample of 542 robust individuals (262 for T1, 205 for T2 and 75 for T3) and a total of 32,520 usable observations for our panel data analysis.

Table 4a (Panel A) contains the main results that we obtain by running a probit model for Treatment 1 in the first column, for Treatment 2 in the second column, and finally for the difference between the parameters estimated for the two treatments in the third column. Starting with Treatment 1, all variables turn out to be highly significant and they all have the expected sign. For example, an increase of the return (r_j) of option A (the bond) has a negative effect on the mutual fund demand, while a higher guaranteed value (g_j) of option B (the fund) increases its demand. Also positively, but in a lower proportion, the upside participation (ρ_j) increases the mutual fund demand. *All these three significant results together statistically confirm our Hypothesis 1.* The negative coefficient of the squared term of the aforementioned upside participation confirms our preliminary graphical analysis, which indicated a concave shape of the demand for the mutual fund as a function of the upside participation. The effects concerning ρ_j and ρ_j^2 deserve a more detailed analysis that we will undergo when we consider the difference between both treatments (third column).

We also find that in a scale from 1 to 12 of risk attitude (1 is very risk averse and 12 is highly risk lover), one additional level in this scale, that is, being characterized as more risk lover, entails a significantly higher probability of choosing the structured fund. *This confirms our Hypothesis 2 that those subjects relatively less risk-averse invest with higher probability in the risky option.*

When we turn to treatment 2 (second column) we observe that all the mentioned significant effects are robust, but they are smaller, with the exception of the effect of the guaranteed return of the fund. But, are these differences in the size of the coefficients significant? In the third column we check for the significance of the differences between the coefficients estimated for the two treatments and we obtain that those for the bond returns, risk aversion and also the intercept are not significantly different between treatments. The positive effect of the guaranteed return of the fund is slightly greater in T2. This is true particularly in the first 30 scenarios when the bond return is relatively low, as we can observe in Panels 4B and 4C. In those panels we separate the sample into the observations of the first 30 and the last 30 scenarios (when ordered as in Table 1).

And the most important differences between the two treatments (third column of Panel 4A) are, firstly, that the positive effect of the upside participation on fund demand is significantly reduced to two thirds in Treatment 2 when the investment options are made harder to compare, thus econometrically confirming the “trend” effect, and secondly, that the concavity of the demand function with respect to this upside participation is also significantly halved for T2, dramatically reducing the “too good to be true” effect (these results are robust for all scenarios as we can observe in panels 4B and 4C). *These two observations together further confirm our Hypothesis 4.*

Table 4a: Treatment Comparison T1 vs T2

Panel Probit Model for the probability of an investor choosing the structured mutual fund

	Panel A (All Scenarios)			**Panel B (Scenarios 1-30)**			**Panel C (Scenarios 31-60)**		
	Treatment 1	Treatment 2	Difference (T2-T1)	Treatment 1	Treatment 2	Difference (T2-T1)	Treatment 1	Treatment 2	Difference(T2-T1)
guaranteed A (r_j)	-0.090***	-0.085***	0.005						
	(0.0021)	(0.0023)	(0.0032)						
guaranteed B (g_j)	0.091***	0.098***	0.008**	0.105***	0.130***	0.025***	0.093***	0.088***	-0.004
	(0.0026)	(0.0029)	(0.0039)	(0.0047)	(0.0052)	(0.0070)	(0.0034)	(0.0037)	(0.0050)
upside percent. (ρ_j)	0.043***	0.028***	-0.013***	0.053***	0.034***	-0.018***	0.038***	0.026***	-0.011***
	(0.0016)	(0.0017)	(0.0024)	(0.0023)	(0.0024)	(0.0033)	(0.0024)	(0.0027)	(0.0037)
ρ_j^2	-0.00022***	-0.0001***	0.00012***	-0.00032***	-0.00014***	0.00017***	-0.00015***	-0.00007***	0.00008***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
risk lover	0.129***	0.087***	-0.041	0.134***	0.098***	-0.035	0.127***	0.079***	-0.045
	(0.0157)	(0.0181)	(0.0253)	(0.0169)	(0.0197)	(0.0272)	(0.0194)	(0.0212)	(0.0312)
constant	-1.275***	-1.041***	0.227	-2.235***	-2.020***	0.196	-3.281***	-2.786***	0.452
	(0.1345)	(0.1577)	(0.2179)	(0.1469)	(0.1739)	(0.2367)	(0.1735)	(0.1915)	(0.2765)
N. Observations	15720	12300	28020	7860	6150	14010	7860	6150	14010
N. Subjects	262	205	467	262	205	467	262	205	467
Wald Chi 2	3775.65***	3037.99***	6818.28***	1461.31***	1339.07***	2808.35***	1750.80***	1297.65***	3050.7***

*(std. error), *** significant at 1%, ** significant at 5%, * significant at 10%.*

Table 4b: Treatment Comparison T1 vs T3

Panel Probit Model for the probability of an investor choosing the structured mutual fund

	Panel D (All Scenarios)			Panel E (Scenarios 1-30)			Panel F (Scenarios 31-60)		
	Treatment 1	Treatment 3	Difference (T3-T1)	Treatment 1	Treatment 3	Difference (T3-T1)	Treatment 1	Treatment 3	Difference(T3-T1)
guaranteed A (r_j)	-0.090***	-0.124***	-0.034***						
	(0.0021)	(0.0052)	(0.0056)						
guaranteed B (g_j)	0.091***	0.111***	0.020***	0.105***	0.097***	-0.008	0.093***	0.129***	-0.036***
	(0.0026)	(0.0060)	(0.0066)	(0.0047)	(0.0103)	(0.0113)	(0.0034)	(0.0082)	(0.0088)
upside percent. (ρ_j)	0.043***	0.046***	0.0041	0.053***	0.055***	0.002	0.038***	0.041***	0.002
	(0.0016)	(0.0034)	(0.0038)	(0.0023)	(0.0048)	(0.0053)	(0.0024)	(0.0057)	(0.0062)
$\rho_j^{\,2}$	-0.00022***	-0.00009***	0.00012***	-0.00032***	-0.00017***	0.00014***	-0.00015***	-0.00002	0.00013***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
risk lover	0.129***	0.038**	-0.168***	0.134***	-0.045**	-0.180***	0.127***	0.036	-0.167***
	(0.0157)	(0.0181)	(0.0267)	(0.0169)	(0.0212)	(0.0289)	(0.0194)	(0.0242)	(0.0341)
constant	-1.275***	-0.390**	0.890***	-2.235***	-1.585***	0.644***	-3.281***	-3.121***	0.157
	(0.1345)	(0.1637)	(0.2242)	(0.1469)	(0.1807)	(0.2430)	(0.1735)	(0.2426)	(0.3132)
N. Observations	15720	4500	20220	7860	2250	10110	7860	2250	10110
N. Subjects	262	75	337	262	75	337	262	75	337
Wald Chi 2	3775.65***	1444.18***	5235.45***	1461.31***	698.25***	2181.66***	1750.80***	693.47***	2460.19***

*(std. error), *** significant at 1%, ** significant at 5%, * significant at 10%.*

Table 4b (Panel D) shows the outcome of a probit regression for Treatment 1 in the first column, for Treatment 3 in the second column, and finally for the difference between the parameters estimated for the two treatments in the third column. Again, as for T1 and T2, all variables turn out to be highly significant and they all have the expected sign. There are only some significant differences between T3 and T1 that can be found in column 3. The increase of the return (r_j) of option A (the bond) has a more negative effect on the mutual fund demand in T1 than in T3, while consistently a higher guaranteed value (g_j) of option B (the fund) increases its demand more in T3 than in T1. Also the constant is a bit less negative reflecting a general higher tendency to invest in the fund in T3. All these three differences indicate us that risky funds are more preferred to the safe bond when the underlying randomness generating process is more transparent. The upside participation shows much lower concavity in T3 than in T1, approximately the same than in T2, confirming a big reduction of the "too good to be true" effect with higher transparency as Hypothesis 5 proposed. On the other hand, no differences are found in the effect of the upside market participation, that is, the "trend" effect, which is equally present in both "ordered" treatments. Risk aversion, as expected, plays a much less fundamental role in T3 with coefficients much closer to zero than in the other two treatments. Observing panels 4E and 4F we see that separating the sample into the two 30 period subsamples does not fundamentally change the results.

In order to try to disentangle the effect of risk aversion in the "too good to be true" effect we have run a Spearman correlation analysis which we present in Table 5. We have shown above that the exact order in which the sequence of upside participations is displayed encourages the trend phenomenon to appear in the treatment with an easier comparison. But still, this would not explain why investment is reduced and not increased for the highest offers. Our hypothesis 3 was that the highly risk-averse subjects will not invest in the mutual fund even for highly favorable expected return differentials. When the upside participation increases highly, the fund's expected return will increase accordingly. But when comparing the options becomes easier, subjects can more easily come to believe that a positive revaluation is more unlikely when they are being offered a relatively high upside participation, and therefore they perceive higher risk if they do not completely trust the computer generated random draw used in T1. It will be fundamentally the more risk-averse who will not want to invest in the fund under these circumstances.

Given that the “too good to be true” effect appears in the last period of every 5 periods cycle, that is, when the premium goes from 100% to 110%, we analyze investors behavior in this scenario interval identifying the ones who choose to invest in the mutual fund when they are offered a 100% over the stock market revaluation and switch to the safe bond investment option when the upside participation increases to 110%.

For Treatment 1 a highly significant negative correlation is observed between the risk loving variable and the frequency with which a subject switches from the mutual fund to the safe option in every fifth period. Thus, a more risk averse attitude is positively correlated with the “too good to be true” effect (see Table 5).

There is no significant correlation in Treatment 2 though, this result being in concordance with our Hypothesis 4, in the sense that the difficulty of comparing the offers makes it harder for our subjects’ minds to spot the extremely high offers and assign them a higher risk. Also there is no significant correlation in Treatment 3, consistent with the our Hypothesis 5 that increased transparency makes subjects trust all offers equally whether more or less risk averse.

Table 5.

Spearman rank correlation between Risk lover and “too good to be true” effect

Rho	Period 1-30	Period 31-60	Period 1-60
Treatment 1	-0.2012***	-0.1269**	-0.2002***
	(0.001)	(0.040)	(0.001)
Treatment 2	-0.0547	-0.1142	-0.0982
	(0.436)	(0.102)*	(0.161)
Treatment 3	-0.1671	-0.0526	-0.1519
	(0.124)	(0.630)	(0.162)

Treatment 1 number of observations: 262 ; Treatment 2 number of observations: 205; Treatment 3 number of observations: 75;

5. Conclusions

In this study we experimentally analyze the demand for structured products; in particular we construct a guaranteed mutual fund that is offered to participant-investors as an alternative to a risk-free bond. Our experimental design allowed us to control for the effect of several variables such as guarantees, upside participation, risk aversion, and the informational structure. We obtain that, apart from the expected rational behavior of participants, consistent with the expected value framework, some behavioral biases arise in Treatment 1, where the investment products are shown sequentially ordered in a way that they can easily be categorized and compared.

One of the behavioral biases observed is a “trend” effect which causes investors to value more positively the structured investment fund when they observe an increase in the expected returns that it offers, even if the final realization of the returns of a given scenario is totally independent of the other scenarios. This illusion is similar to other well known behavioral biases in the literature such as the “illusion of past returns”. We believe this can only be fought by the regulator with greater financial literacy and an insistence that past returns are not a guarantee of future returns.

Another behavioral bias, first documented here, is what we call the “too good to be true” effect. This refers to participants not investing in extremely high yields opportunities that seem hard to believe. This appears to be a consequence of investors being able to more easily compare the different investment alternatives, thus altering their perceived risk, as it disappears when we present the investment scenarios in random order in T2. Also, a modification of the design in T3, which makes transparent to the subjects the generation of the random market revaluation, keeping the perceived risk constant for all upside participations, results in the “too good to be true” effect being greatly reduced, without the need of presenting the scenarios in random order.

A policy implication of our main experimental finding would call for increasing the availability of directly comparable investments that the investors could study before placing their money. Regulation in the structured funds industry should control the way this information is presented to investors to prevent financial advisers exploiting behavioral biases in order to favor their own products. Simplifying the investors' information processing load could reduce the probability of their getting lured into dubious investments. Besides, exposing dark spots in the information about how the returns will be generated can importantly help the investor to identify unreasonable offers (e.g. a Ponzi scheme).

Future research could explore the effectiveness of offering all information ordered, categorized and clearly explained beforehand in fighting the trend bias while at the same time discouraging the "too good to be true" bias by transparently generating the random market revalorization. Also, exploring whether introducing a decreasing expected return ordering produces a penalizing effect for the funds would possibly be worth further investigation.

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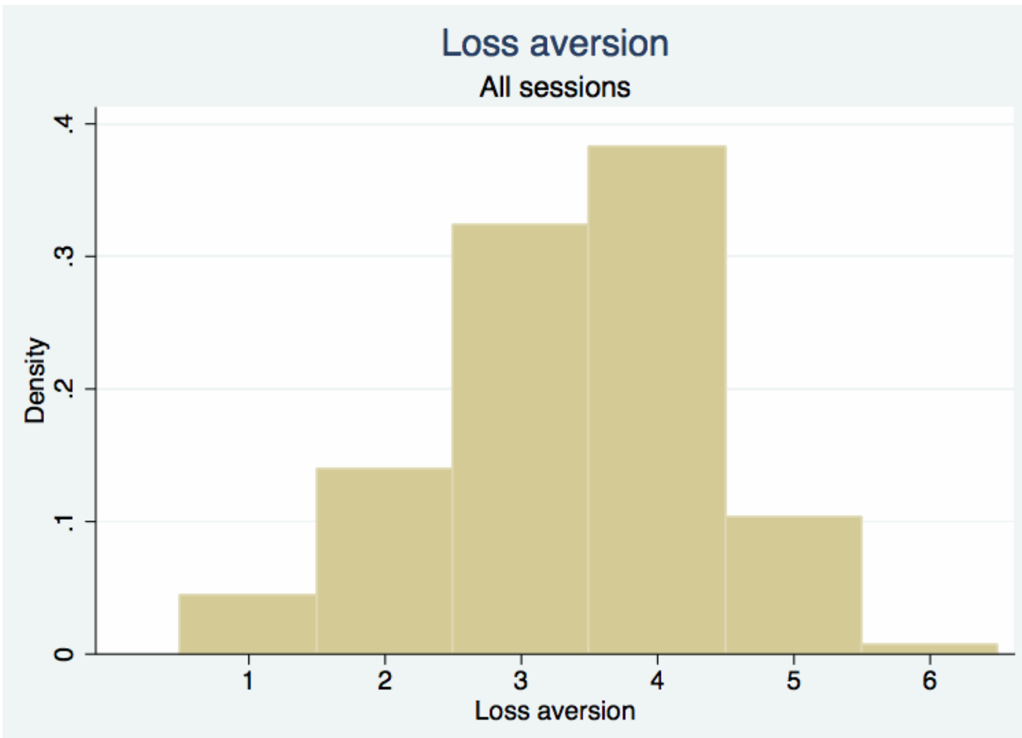
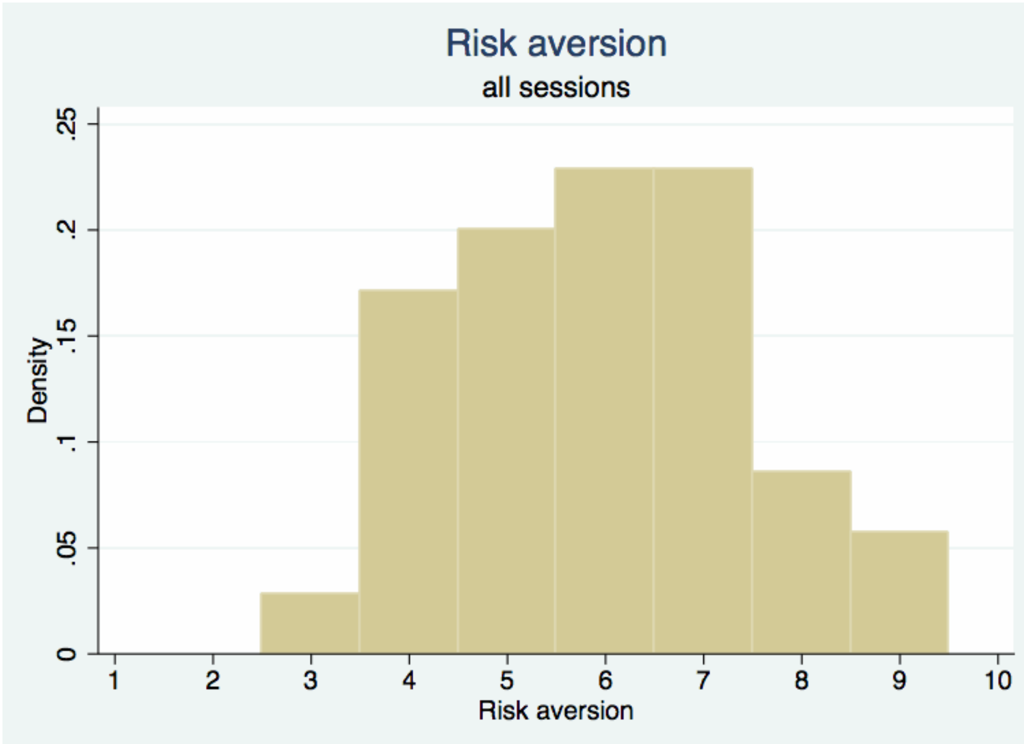
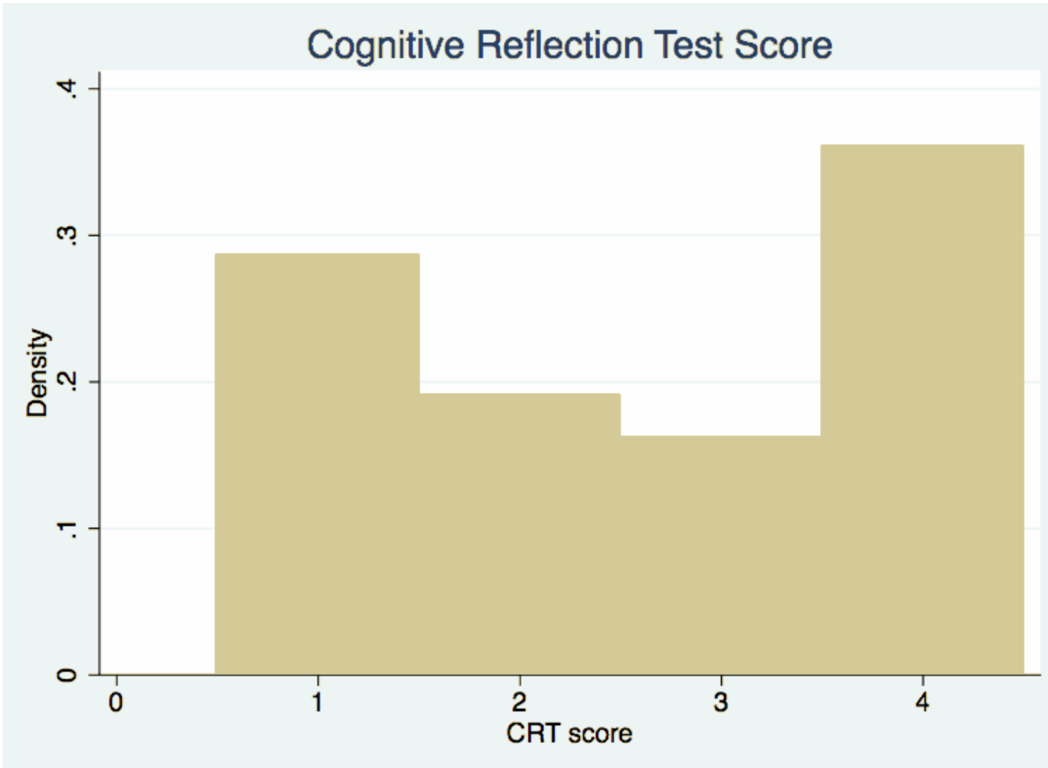
Appendix Chapter 1:

Appendix 1.I: histograms of the distributions of Loss Aversion, Risk Aversion and Cognitive Reflection Test Scores among our subjects.




Risk aversion
all sessions
Density
0
.05
.1
.15
.2
.25
1
2
3
4
5
6
7
8
9
10
Risk aversion


Cognitive Reflection Test Score
Density
0
.1
.2
.3
.4
0
1
2
3
4
CRT score

Appendix 1.II: Instructions Decreasing Fundamental Value Treatment:

General Instructions

Welcome to this experiment. The instructions are simple and if you follow them carefully and make good decisions, you might earn a considerable amount of money, which will be paid to you in cash at the end of the experiment.

The session will be divided in four parts and you will have the opportunity to earn money in each of them.

Part I

In the first part of the experiment six bets will be presented to you. Each bet gives you a 50-50 chance of winning some money or losing some money.

For each bet, you must decide if you want to play it or not, although only one randomly chosen decision will count toward your earnings.

After all participants have made their decisions for each of the six bets, the experimenter will roll a six-sided die. The outcome of the roll will determine the one single bet that will count to determine your earnings. If the die reads 1, you will be paid for your decision in the first lottery. If the die reads 2, you will be paid for your decision in the second lottery, and so on. Exactly one of the six bets will count.

After the die is rolled, if you decided not to play the bet chosen by the die roll, your earnings will be 0 euros for this part of the experiment.

If you decided to play that bet chosen by the die roll, there will be a 50-50 chance for you to win or lose the amount of money indicated in the bet. Then, the experimenter will toss a coin. If the coin comes up heads you lose and if the coin comes up tails you win the amount of money specified in the lottery.

Lottery (50-50 chance)	**Accept to play?**	
Lose 0.5€ or win 4.5€	Yes	No
Lose 1.5€ or win 4.5€	Yes	No
Lose 2.5€ or win 4.5€	Yes	No
Lose 3.5€ or win 4.5€	Yes	No
Lose 4.5€ or win 4.5€	Yes	No
Lose 5.5€ or win 4.5€	Yes	No

Part II

In this part of the experiment, you will have to answer three questions. You will have exactly 3 minutes to answer the questions. Each correct answer will earn you 1 euro. That is, if you give one correct answer, you get 1 euro; if you give two correct answers you get 2 euros and if you give three correct answers you get 3 euros in this part of the experiment. There is no penalty for wrong answers.

Part III

In this part of the experiment you will be making choices between two lotteries, such as those represented as "Option A" and "Option B" below. The money prizes are determined by the computer equivalent of throwing a ten-sided die. Each outcome, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, is equally likely. If you choose Option A in the row shown below, you will have a 1 in 10 chance of earning 2.00€ and a 9 in 10 chance of earning 1.60€. Similarly, Option B offers a 1 in 10 chance of earning 3.85€ and a 9 in 10 chance of earning 0.10€.

1st:

Option A: 2.00€ if the die is 1 and 1.60€ if the die is 2 - 10
Option B: 3.85€ if the die is 1 and 0.10€ if the die is 2 – 10

Each box of the decision table contains a pair of choices between Option A and Option B. You make your choice by clicking on the "A" or "B" buttons on the bottom. Only one option in each box can be selected, and you may change your decision as you wish.
Note: try clicking on one of the radio buttons, then change by clicking on the other one.

Even though you will make ten decisions, only one of these will end up being used. The selection of the one to be used depends on the "throw of the die" that is the determined by the computer's random number generator. No decision is any more likely to be used than any other, and you will not know in advance which one will be selected, so please think about each one carefully.
For example, suppose that you make all ten decisions and the roll of the die is 9, then your choice, A or B, for decision 9 would be used and the other decisions would not be used.

After the random die throw determines the decision box that will be used, we need to obtain a second random number that determines the earnings for the option you chose for that box. In Decision 9 below, for example, a throw of 1, 2, 3, 4, 5, 6, 7, 8, or 9 will result in the higher payoff for the option you chose, and a throw of 10 will result in the lower payoff.

9th:

Option A: 2.00€ if the die is 1-9 and 1.60€ if the die is 10
Option B: 3.85€ if the die is 1-9 and 0.10€ if the die is 10

For decision 10, the random die throw will not be needed, since the choice is between amounts of money that are fixed: 2.00€ for Option A and 3.85€ for Option B.

Your earnings in this part of the experiment will be added to your final payoff.

Part IV

In this part of the experiment you will make decisions in a market. There will be a sequence of trading periods in which you will have the opportunity to buy and sell shares in a market. The currency used in this market is ECU. All trading will be in terms of ECU. The cash payment to you at the end of the experiment will be in Euros. The conversion rate is 500 ECU to 1 Euro.

1. How to use the computerized market

On the top right corner of the screen you see how much time is left in the current period. The goods that can be bought and sold in the market are called Shares. On the left side of your screen you see the current period, the number of Shares you currently have and the amount of Money, in ECU, you have available to buy Shares.

If you would like to offer to sell a share, use the text area entitled “Enter offer to sell:” in the second column. In that text area you can enter the price at which you are offering to sell a Share, and then select “Submit Offer To Sell”. Please do so now. Type in a number in the appropriate space, and then click on the field labelled “Submit Offer To Sell”. You will notice that nine numbers, one submitted by each participant, now appear in the second column on the left, entitled “Offers To Sell”. Your offer is listed in blue. Submitting a second offer will replace your previous offer.

The lowest offer-to-sell price will always be on the top of that list and will, by default, be selected. You can select a different offer by clicking on it. It will then be highlighted. If you select “Buy”, the button at the bottom of this column, you will buy one share for the currently selected sell price. Please purchase a share now by selecting “Buy” button. Since each of you had offered to sell a share and attempted to buy a share, if all were successful, you will all have the same number of shares you started out with. This is because you bought one share and sold one share. Please note that if you have an offer selected and the offer gets changed, it will become deselected if the offer became worse for you. If the offer gets better, it will remain selected.

When you buy a share, your Money decreases by the price of the purchase. When you sell a share, your Money increases by the price of the sale. You may make an offer to buy a unit by selecting “Submit offer to buy”. Please do so now. Type a number in the text area“Enter offer to buy, then press the red button labelled “Submit Offer to buy”. You can replace your offer-to-buy by submitting a new offer. You can accept any of the offers-to-buy by selecting the offer and then clicking on the “Sell” button. Please do so now.

In the middle column, labelled “Transaction Prices”, you can see the prices at which Shares have been bought and sold in this period. You will now have 5 minutes to buy and sell shares. This is a practice period. Your actions in the practice period do not count toward your earnings and do not influence your position later in the experiment. The only goal of the practice period is to master the use of the interface. Please be sure that you have successfully submitted offers to buy and offers to sell. Also be sure that you have accepted to buy and sell others. You are free to ask questions during the practice period by raising your hand.

2. Specific Instructions for this experiment

The experiment will consist of 15 trading periods. In each period, there will be a market open for 2 minutes, during which you are permitted to buy and sell shares. Shares have life of 15 periods. Your inventory of shares carries over from one period to the next. For example, if you have 5 shares at the end of period 1, you will have 5 shares at the beginning of period 2.

You start period 1 with 10 shares in your inventory and 3600 ECU of Money balance, which you can use in the market.

Dividends:

You may receive dividends for each share in your inventory at the end of each of the 15 trading periods. At the end of each trading period, including period 15, the experimenter will flip a coin, which will determine the dividend for that period.

Each period, each share you hold at the end of the period earns you a dividend of:

10 ECU if the coin comes up heads
-10 ECU if the coin comes up tails

Both sides of the coin are equally likely, which means that the average dividend is 0. We arrive at 0 by averaging the two equally likely dividends: 10, -10. That is, we calculate (10-10)/2=0.

If the dividend of the period is 10, you earn 10 ECU for each share you own, and that money will be automatically added to your Money balance at the end of the period. If the dividend of the period is -10, for each share you own there will be 10 ECU subtracted from your Money balance at the end of the period.

Subsidies: At the end of each of the last eight periods, you will obtain a payment of 10 ECU for each share in your inventory. This payment is called a subsidy. The subsidy is paid to you at the end of period 8, period 9, ..., and period 15. No subsidy is paid at the end of the first seven periods: period 1, period 2,..., and period 7.

The subsidies that you receive are automatically added to your money balance at the end of each of the last eight periods.

Final Buyout: At the end of period 15, after the dividends and subsidies have been paid out for the period, the experimenter will purchase back all the shares in the market for 40 ECU each from their current owners. This buyout value will be added to any dividends and subsidies received in period 15.

3. Average Holding Value Table

You can use the AVERAGE HOLDING VALUE TABLE (attached at the end of this document) to help you make decisions. It calculates the average amount of dividends and holding taxes you will receive and pay if you keep a share until the end of the experiment. It also describes how to calculate how much in future dividends and holding taxes you give up on average when you sell a share at any time. The columns in the table contain the following information:

1. Current Period: the period during which the average holding is being calculated. For example, in period 1, the numbers in the row corresponding to "Current Period 1" are in effect.
2. Number of Remaining Dividends: the number of times that a dividend can be received from the current period until the final period. This is the remaining number of times the experimenter will toss the coin. It is calculated by taking the total number of periods, 15, subtracting the current period number, and adding 1, because the dividend is also paid in the current period.
3. Average Dividend: the average amount of each dividend. As we indicated earlier, the average dividend in each period is 0 per share in each period.
4. Final buyout Value: The payment you receive for each share you hold at the end of period 15.
5. 5. Number of Remaining Subsidy Payments: the number of times that a subsidy will be paid on a share from the current period until the end of the experiment. It is calculated by taking the total number of subsidies periods, 8, and subtracting the number of subsidies periods that have already passed.
6. Subsidy Amount per period: the amount that the subsidy payment per share will be in the current period. As indicated earlier, there is no subsidy in the first 7 periods, while the subsidy amount is 10 ECU per share in the last 8 periods.
7. Total Remaining Subsidies: the total value of the subsidies remaining on a share from now until the end of the experiment. That is, for each unit you hold in your inventory for the remainder of the experiment, you will be paid the amount listed in column 7 in holding subsidies. It is calculated by multiplying Number of Remaining Subsidies Payments by Subsidy Amount.
8. Average Holding Value: the average value of holding a share for the remainder of the experiment. That is, for each unit you hold in your inventory for the remainder of the experiment, the net value of the dividends you earn, the subsidies you will be paid and the buyout value you receive will on average be the amount listed here. It is calculated by summing up Remaining Subsidies, Average Remaining Dividends and the Final Buyout Value.

4. Your Earnings

Your earnings in this part of the experiment will equal the total amount of money that you have at the end of period 15. More specifically, your earnings will be:

the money you begin with
+any dividends you receive
+any subsidies you receive
+any money you receive from sales of shares
-any money you spend on purchases of shares
+ the final buyout value for the units you have at the end of period 15
Please have a look at this table now and make sure you understand it. Feel free to raise your hand if you have a question. When you feel confortable with it, please go on and answer the following practice quiz:

PRACTICE QUIZ

1. Suppose it is period 10. How much will you get paid in total in subsidies on a share if you hold it for the remainder of the experiment?

   ANSWER:

2. Suppose it is period 10. How much do you expect to receive in dividends on a share if you hold it for the remainder of the experiment?

   ANSWER:

3.Suppose it is period 10. What is the average value of holding a share for the remainder of the experiment?

ANSWER:

Beginning the experiment. From now on your decisions will count toward your earnings, so please think carefully before making them.

Average Holding Value Table

Current Period	Number of Remaining Dividends	Average Dividend	Final Buyout Value	Number of Remaining Subsidy payments	Subsidy Amount	Remaining Subsidies	Average Holding Value
1	15	0	40	8	0	80	120
2	14	0	40	8	0	80	120
3	13	0	40	8	0	80	120
4	12	0	40	8	0	80	120
5	11	0	40	8	0	80	120
6	10	0	40	8	0	80	120
7	9	0	40	8	0	80	120
8	8	0	40	8	10	80	120
9	7	0	40	7	10	70	110
10	6	0	40	6	10	60	100
11	5	0	40	5	10	50	90
12	4	0	40	4	10	40	80
13	3	0	40	3	10	30	70
14	2	0	40	2	10	20	60
15	1	0	40	1	10	10	50

Appendix 1.III: Instructions Increasing Fundamental Value Treatment:

General Instructions

Welcome to this experiment. The instructions are simple and if you follow them carefully and make good decisions, you might earn a considerable amount of money, which will be paid to you in cash at the end of the experiment.

The session will be divided in four parts and you will have the opportunity to earn money in each of them.

Part I

In the first part of the experiment six bets will be presented to you. Each bet gives you a 50-50 chance of winning some money or losing some money.

For each bet, you must decide if you want to play it or not, although only one randomly chosen decision will count toward your earnings.

After all participants have made their decisions for each of the six bets, the experimenter will roll a six-sided die. The outcome of the roll will determine the one single bet that will count to determine your earnings. If the die reads 1, you will be paid for your decision in the first lottery. If the die reads 2, you will be paid for your decision in the second lottery, and so on. Exactly one of the six bets will count.

After the die is rolled, if you decided not to play the bet chosen by the die roll, your earnings will be 0 euros for this part of the experiment.

If you decided to play that bet chosen by the die roll, there will be a 50-50 chance for you to win or lose the amount of money indicated in the bet. Then, the experimenter will toss a coin. If the coin comes up heads you lose and if the coin comes up tails you win the amount of money specified in the lottery.

Lottery (50-50 chance)	**Accept to play?**	
Lose 0.5€ or win 4.5€	Yes	No
Lose 1.5€ or win 4.5€	Yes	No
Lose 2.5€ or win 4.5€	Yes	No
Lose 3.5€ or win 4.5€	Yes	No
Lose 4.5€ or win 4.5€	Yes	No
Lose 5.5€ or win 4.5€	Yes	No

Part II

In this part of the experiment, you will have to answer three questions. You will have exactly 3 minutes to answer the questions. Each correct answer will earn you 1 euro. That is, if you give one correct answer, you get 1 euro; if you give two correct answers you get 2 euros and if you give three correct answers you get 3 euros in this part of the experiment. There is no penalty for wrong answers.

Part III

In this part of the experiment you will be making choices between two lotteries, such as those represented as "Option A" and "Option B" below. The money prizes are determined by the computer equivalent of throwing a ten-sided die. Each outcome, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, is equally likely. If you choose Option A in the row shown below, you will have a 1 in 10 chance of earning 2.00€ and a 9 in 10 chance of earning 1.60€. Similarly, Option B offers a 1 in 10 chance of earning 3.85€ and a 9 in 10 chance of earning 0.10€.

1st:
Option A: 2.00€ if the die is 1 and 1.60€ if the die is 2 - 10
Option B: 3.85€ if the die is 1 and 0.10€ if the die is 2 – 10

Each box of the decision table contains a pair of choices between Option A and Option B. You make your choice by clicking on the "A" or "B" buttons on the bottom. Only one option in each box can be selected, and you may change your decision as you wish.
Note: try clicking on one of the radio buttons, then change by clicking on the other one.

Even though you will make ten decisions, only one of these will end up being used. The selection of the one to be used depends on the "throw of the die" that is the determined by the computer's random number generator. No decision is any more likely to be used than any other, and you will not know in advance which one will be selected, so please think about each one carefully.

For example, suppose that you make all ten decisions and the roll of the die is 9, then your choice, A or B, for decision 9 would be used and the other decisions would not be used.

After the random die throw determines the decision box that will be used, we need to obtain a second random number that determines the earnings for the option you chose for that box. In Decision 9 below, for example, a throw of 1, 2, 3, 4, 5, 6, 7, 8, or 9 will result in the higher payoff for the option you chose, and a throw of 10 will result in the lower payoff.

9th:
Option A: 2.00€ if the die is 1-9 and 1.60€ if the die is 10
Option B: 3.85€ if the die is 1-9 and 0.10€ if the die is 10

For decision 10, the random die throw will not be needed, since the choice is between amounts of money that are fixed: 2.00€ for Option A and 3.85€ for Option B.

Your earnings in this part of the experiment will be added to your final payoff.

Part IV

In this part of the experiment you will make decisions in a market. There will be a sequence of trading periods in which you will have the opportunity to buy and sell shares in a market. The currency used in this market is ECU. All trading will be in terms of ECU. The cash payment to you at the end of the experiment will be in Euros. The conversion rate is 500 ECU to 1 Euro.

1. **How to use the computerized market**

On the top right corner of the screen you see how much time is left in the current period. The goods that can be bought and sold in the market are called Shares. In the center of your screen you see the current period and the amount of Money, in ECU, you have available to buy Shares. To the left of the screen, you see the number of Shares you currently have.

If you would like to offer to sell a share, use the text area entitled “Enter offer to sell:” in the second column. In that text area you can enter the price at which you are offering to sell a Share, and then select “Submit Offer To Sell”. Please do so now. Type in a number in the appropriate space, and then click on the field labelled “Submit Offer To Sell”. You will notice that nine numbers, one submitted by each participant, now appear in the third column on the left, entitled “Offers To Sell”. The lowest ask price will always be on the bottom of that list and will, by default, be selected. You can select a different offer by clicking on it. If you select “Buy”, the button at the bottom of this column, you will buy one share for the currently selected sell price.

Please purchase a share now by selecting “Buy”. Since each of you had offered to sell a share and attempted to buy a share, if all were successful, you will all have the same number of shares you started out with. This is because you bought one share and sold one share.

When you buy a share, your Money decreases by the price of the purchase. When you sell a share, your Money increases by the price of the sale. You may make an offer to buy a unit by selecting “Submit offer to buy”. Please do so now. Type a number in the text area “Enter offer to buy”. Then press the red button labelled “Submit Offer to buy”. You can sell to the person who submitted the highest offer to buy if you click on “Sell”. Please do so now.

In the middle column, labelled “Transaction Prices”, you can see the prices at which Shares have been bought and sold in this period.

You will now have 10 minutes to buy and sell shares. This is a practice period. Your actions in the practice period do not count toward your earnings and do not influence your position later in the experiment. The only goal of the practice period is to master the use of the interface. Please be sure that you have successfully submitted offers to buy and offers to sell. Also be sure that you have accepted to buy and sell others. You are free to ask questions during the practice period by raising your hand.

2. Specific Instructions for this experiment

The experiment will consist of 15 trading periods. In each period, there will be a market open for 2 minutes, during which you are permitted to buy and sell shares. Shares have life of 15 periods. Your inventory of shares carries over from one period to the next. For example, if you have 5 shares at the end of period 1, you will have 5 shares at the beginning of period 2.

You start period 1 with 10 shares in your inventory and 3600 ECU of Money balance, which you can use in the market.

Dividends:

You may receive dividends for each share in your inventory at the end of each of the 15 trading periods. At the end of each trading period, including period 15, the experimenter will flip a coin, which will determine the dividend for that period.

Each period, each share you hold at the end of the period earns you a dividend of:

10 ECU if the coin comes up heads
-10 ECU if the coin comes up tails

Both sides of the coin are equally likely, which means that the average dividend is 0. We arrive at 0 by averaging the two equally likely dividends: 10, -10. That is, we calculate (10-10)/2=0.

If the dividend of the period is 10, you earn 10 ECU for each share you own, and that money will be automatically added to your Money balance at the end of the period. If the dividend of the period is -10, for each share you own there will be 10 ECU subtracted from your Money balance at the end of the period.

Taxes: At the end of each of the last eight periods, you must pay a tax of 10 ECU for each share you have. That is, a tax is paid at the end of period 8, period 9,…, and period 15. No tax is paid at the end of the first seven periods: period 1, period 2,…, and period 7.

The taxes you owe on shares are automatically subtracted from your money balance at the end of each of the last eight periods.

Final Buyout: At the end of period 15, after the dividends and taxes have been paid out, the experimenter will purchase back all the shares in the market for 200 ECU each from their current owners. This buyout value will be added to any dividends received in period 15.

3. Average Holding Value Table

You can use the AVERAGE HOLDING VALUE TABLE (attached at the end of this document) to help you make decisions. It calculates the average amount of dividends and holding taxes you will receive and pay if you keep a share until the end of the experiment. It also describes how to calculate how much in future dividends and holding taxes you give up on average when you sell a share at any time.

1. Current Period: the period during which the average holding is being calculated. For example, in period 1, the numbers in the row corresponding to "Current Period 1" are in effect.
2. Number of Remaining Dividends: the number of times that a dividend can be received from the current period until the final period. That is, it indicates the remaining number of times the experimenter will toss the coin. It is calculated by taking the total number of periods, 15, subtracting the current period number, and adding 1, because the dividend is also paid in the current period.
3. Average Dividend: the average amount of each dividend. As we indicated earlier, the average dividend in each period is 0 per share in each period.
4. Final buyout Value: The payment you receive for each share you hold at the end of period 15.
5. Number of Remaining Tax Payments: the number of times that a tax must be paid on a share from the current period until the end of the experiment. It is calculated by taking the total number of tax periods, 8, and subtracting the number of tax periods that have already passed.
6. Tax Amount: the amount that the tax payment per share will be. As indicated earlier, there is no tax in the first 7 periods, while the tax amount is 10 ECU per share in the last 8 periods.
7. Remaining Taxes: the total value of the taxes remaining on a share from now until the end of the experiment. That is, for each unit you hold in your inventory for the remainder of the experiment, you will pay the amount listed in column 7 in holding taxes. It is calculated by multiplying Number of Remaining Tax Payments by Tax Amount.
8. Average Holding Value: the average value of holding a share for the remainder of the experiment. That is, for each unit you hold in your inventory for the remainder of the experiment, the difference between the dividends you earn and the taxes you pay will on average be the amount listed here. It is calculated by subtracting Remaining Taxes from Average Remaining Dividends.

Please have a look at this table now and make sure you understand it. Feel free to raise your hand if you have a question. When you feel comfortable with it, please go on and answer the following practice quiz:

PRACTICE QUIZ

1. Suppose it is period 10. How much will you pay in total in taxes on a share if you hold it for the remainder of the experiment?

   ANSWER:

2. Suppose it is period 10. How much do you expect to receive in dividends on a share if you hold it for the remainder of the experiment?

   ANSWER:

3. Suppose it is period 10. What is the average value of holding a share for the remainder of the experiment?

   ANSWER:

4. Your Earnings

Your earnings in this part of the experiment will equal the total amount of money that you have at the end of period 15. More specifically, your earnings will be:

the money you begin with
+any dividends you receive
-any taxes you pay
+any money you receive from sales of shares
-any money you spend on purchases of shares

Beginning the experiment. From now on your decisions will count toward your earnings, so please think carefully before making them.

Average Holding Value Table

Current Period	Number of Remaining Dividends	Average Dividend	Final Buyout Value	Number of Remaining Tax Payments	Tax Amount	Remaining Taxes	Average Holding Value
1	15	0	200	8	0	80	120
2	14	0	200	8	0	80	120
3	13	0	200	8	0	80	120
4	12	0	200	8	0	80	120
5	11	0	200	8	0	80	120
6	10	0	200	8	0	80	120
7	9	0	200	8	0	80	120
8	8	0	200	8	10	80	120
9	7	0	200	7	10	70	130
10	6	0	200	6	10	60	140
11	5	0	200	5	10	50	150
12	4	0	200	4	10	40	160
13	3	0	200	3	10	30	170
14	2	0	200	2	10	20	180
15	1	0	200	1	10	10	190

Appendix Chapter 2:

APPENDIX 2.I: Instructions for the Loss Aversion Measurement Task

Welcome to this experiment. The instructions are simple and if you follow them carefully and make good decisions, you might earn a considerable amount of money, which will be paid to you by bank transfer at the end of the experiment.

The session will be divided in two parts and you will have the opportunity to earn money in both of them.

Part I

In the first part of the experiment six bets will be presented to you. Each bet gives you a 50-50 chance of winning some money or losing some money.

For each bet, you must decide if you want to play it or not, although only one randomly chosen decision will count toward your earnings.

After all participants have made their decisions for each of the six bets, the experimenter will roll a six-sided die. The outcome of the roll will determine the one single bet that will count to determine your earnings. If the die reads 1, you will be paid for your decision in the first lottery. If the die reads 2, you will be paid for your decision in the second lottery, and so on. Exactly one of the six bets will count.

After the die is rolled, if you decided not to play the bet chosen by the die roll, your earnings will be 0 euros for this part of the experiment.

If you decided to play that bet chosen by the die roll, there will be a 50-50 chance for you to win or lose the amount of money indicated in the bet. Then, the experimenter will toss a coin for each participant. If the coin comes up heads you lose and if the coin comes up tails you win the amount of money specified in the lottery.

Lottery (50-50 chance)	Accept to play?	
Lose 0.5€ or win 4.5€	Yes	No
Lose 1.5€ or win 4.5€	Yes	No
Lose 2.5€ or win 4.5€	Yes	No
Lose 3.5€ or win 4.5€	Yes	No
Lose 4.5€ or win 4.5€	Yes	No
Lose 5.5€ or win 4.5€	Yes	No

APPENDIX 2.II: Instructions for the Asset Market

1. General Instructions

The second part of the experiment consists of a sequence of trading Periods in which you will have the opportunity to buy and sell in a market. The currency used in the market is ECU. All trading will be done in terms of ECU. The final payment to you at the end of the experiment will be in euros. The conversion rate is: **500 ECU to 1 euro.**

2. How to use the computerized market

In the top right hand corner of the screen you see how much time is left in the current trading Period. The goods that can be bought and sold in the market are called Shares. On the left side of your screen you see the number of Shares you currently have and the amount of Money you have available to buy Shares.

If you would like to offer to sell a share, use the text area entitled "Enter offer to sell" in the first column. In that text area you can enter the price at which you are offering to sell a share, and then select "Submit Offer To Sell". Please do so now. Type in a number in the appropriate space, and then click on the field labeled "Submit Offer To Sell". You will notice that nine numbers, one submitted by each participant, now appear in the second column from the left, entitled "Offers To Sell". Your offer is listed in blue. Submitting a second offer will replace your previous offer.

The lowest offer-to-sell price will always be on the bottom of that list. You can select an offer by clicking on it. It will then be highlighted. If you select "Buy", the button at the bottom of this column, you will buy one share for the currently selected sell price. Please purchase a share now by selecting an offer and clicking the "Buy" button. Since each of you had offered to sell a share and attempted to buy a share, if all were successful, you all have the same number of shares you started out with. This is because you bought one share and sold one share. Please note that if you have an offer selected and the offer gets changed, it will become deselected if the offer became worse for you. If the offer gets better, it will remain selected.

When you buy a share, your Money decreases by the price of the purchase. When you sell a share your Money increases by the price of the sale. You may make an offer to buy a unit by selecting "Submit offer to buy." Please do so now. Type a number in the text area "Enter offer to buy", then press the red button labeled "Submit Offer To Buy". You can replace your offer-to-buy by submitting a new offer. You can accept any of the offers-to-buy by selecting the offer and then clicking on the "Sell" button. Please do so now.

In the middle column, labeled "Transaction Prices", you can see the prices at which Shares have been bought and sold in this period. You will now have about 5 minutes to buy and sell shares. This is a practice period. Your actions in the practice period do not count toward your earnings and do not influence your position later in the experiment. The only goal of the practice period is to master the use of the interface. Please be sure that you have successfully submitted offers to buy and offers to sell. Also be sure that you have accepted buy and sell offers. If you have any questions, please raise your hand and the experimenter will come by and assist you.

3. Specific Instructions for this experiment

The experiment will consist of 15 trading periods. In each period, there will be a market open for 2 minutes, in which you may buy and sell shares. Shares are assets with a life of 15 periods, and your inventory of shares carries over from one trading period to the next. You may receive dividends for each share in your inventory at the end of each of the 15 trading periods.

At the end of each trading period, including period 15, the computer will randomly determine the dividend value for all shares in that period. Each period, each share you hold at the end of the period:

earns you a dividend of 0 ECU with a ¼ chance

earns you a dividend of 8 ECU with a ¼ chance

earns you a dividend of 28 ECU with a ¼ chance

earns you a dividend of 60 ECU with a ¼ chance

Each of the four dividend values is equally likely, thus the average dividend in each period is 24. Dividends are added to your cash balance automatically.

After the dividend is paid at the end of period 15, there will be no further earnings possible from shares.

4. Average Holding Value Table

You can use your AVERAGE HOLDING VALUE TABLE to help you make decisions. There are 5 columns in the table. The first column, labeled Ending Period, indicates the last trading period of the experiment. The second column, labeled Current Period, indicates the period during which the average holding value is being calculated. The third column gives the number of holding periods from the period in the second column until the end of the experiment. The fourth column, labeled Average Dividend per Period, gives the average amount that the dividend will be in each period for each unit held in your inventory. The fifth column, labeled Average Holding Value Per Unit of Inventory, gives the average value for each unit held in your inventory from now until the end of the experiment. That is, for each share you hold for the remainder of the experiment, you will earn on average the amount listed in column 5.

Suppose for example that there are 7 periods remaining. Since the dividend on a Share has a 25% chance of being 0, a 25% chance of being 8, a 25% chance of being 28 and a 25% chance of being 60 in any period, the dividend is on average 24 per period for each Share. If you hold a Share for the remaining 7 periods, the total dividend for the Share over the 7 periods is on average 7*24 = 168. Therefore, the total value of holding a Share over the 7 periods is on average 168

AVERAGE HOLDING VALUE TABLE

Ending Period	Curent Period	Number of Remaining Periods	Average Dividend per Period	Average Holding Value per Unit of Inventory
15	1	15	24	15x24=360
15	2	14	24	14x24=336
15	3	13	24	13x24=312
15	4	12	24	12x24=288
15	5	11	24	11x24=264
15	6	10	24	10x24=240
15	7	9	24	9x24=216
15	8	8	24	8x24=192
15	9	7	24	7x24=168
15	10	6	24	6x24=144
15	11	5	24	5x24=120
15	12	4	24	4x24=96
15	13	3	24	3x24=72
15	14	2	24	2x24=48
15	15	1	24	1x24=24

5. Your Earnings

Your earnings for this part of the experiment will equal the amount of cash that you have at the end of period 15, after the last dividend has been paid. The amount of cash you will have is equal to:

The cash (called "Money" on your screen) you have at the beginning of the experiment

+ dividends you receive

+ money received from sales of shares

- money spent on purchases of shares

Appendix Chapter 4:

APPENDIX 4.I: Instructions

Welcome to this experiment.

This is an economic experiment about investment in financial products. The instructions are simple and if you follow them carefully you can earn a considerable amount of money. Your earnings are confidential and will be paid to you in cash at the end of the experiment.

Your earnings will consist of two parts: your profits in the first and the second part of the experiment.

Your personal information will be treated confidentially and will not be used for purposes unrelated to this experiment and your name will never be associated with any of your decisions when the results are published. Do not reveal your decisions to any other participant during the experimental session; communication with other participants in the experiment will automatically entail cero gain for participants who violate this rule.

The experimental unit (EU) is the currency used in the experiment, so that investments, lotteries, etc., will be expressed in terms of EU. At the end of the experiment the amount of EU you earn will be converted to euros using the following exchange rate: 8.000 EU = 1 €. Keep in mind that the more EU you win, the more euros you will get.

This economic experiment consists of three parts:

1 - experimental session of 60 scenarios in which you will choose between two alternative investments.
2 - lotteries session in which again you must choose under different situations.
3 - questionnaire.

1. FIRST PART OF THE EXPERIMENT

The main experiment consists of 60 scenarios. In each scenario, you will have to choose one alternative investment for an amount of 100,000 EU and a three years time horizon.

In each scenario there are two possible investment alternatives: A and B. The conditions for A and B alternatives may vary across scenarios.

Your earnings in this part of the experiment will be the outcome of the investment you've chosen in one of the 60 scenarios. The particular scenario will be randomly chosen casting a die after the experiment ends. So you should think carefully about each scenario, since the decision you make in one of them will determine your earnings in this part of the experiment.

The following explains each of the investment alternatives:

<u>Alternative A</u>

Alternative A is to invest in a Treasury Bond. If you choose this option, the 100,000 EU will be invested in risk free financial product that guarantees the safe 100% recovery of the investment, and offering in addition a fixed return. The information appearing on your computer screen is for example as follows:

Option A

109.000 EU
Equivalent to 109% of the investment:

The table shows the amount of EU you would get after 3 years. That is, if you invest 100,000 EU today, within three years you would safely get 109,000 EU. Below, the table reports how this result can be interpreted. So, investing 100,000 EU and obtaining 109,000 EU is equivalent to getting 109% of the initial investment. This percentage is composed of two elements: 100% recovery of initial investment plus 9% interest rate in 3 years, that is to say 3% annual yield.

Another example of option A is shown below:

Option A

121.000 EU
Equivalent to 121% of the investment

That is to say, if you invest 100,000 EU you would safely obtain 121,000 EU within 3 years. This means you get 121% of the amount you invested. This percentage is composed of two elements: 100% recovery of the investment and a 21% interest rate in 3 years, that is to say a 7% annual yield.

<u>Alternative B</u>

As it has already been mentioned in each scenario you will have to choose between alternative A and alternative B. Just like option A, option B consists of investing the 100,000 EU amount for three years period, but in a guaranteed investment fund.

This financial product guarantees obtaining within three years a certain percentage of the amount initially invested. In addition, the investor will be able to obtain an additional benefit if the stock index presents a positive evolution. This additional benefit is uncertain because it depends on the evolution of the stock market.

For example, there is a table containing the information of a certain alternative B of one of the 60 scenarios:

Option B

97.000 EU
Equivalent to 97% of the investment:
97% recovery of the investment

This table shows that if you invest the 100,000 EU in the guaranteed mutual fund, within three years you would obtain the following:

i) On one hand you obtain 97,000 EU. That is to say you will recover 97% of your investment for sure.

ii) On the other hand, you obtain a 10% over the positive revaluation of the stock index during the three years. The issue, of course, is that you do not know what the future revaluation of the index will be. Therefore, this means that part of the final outcome of option B will always be probabilistic.

Once you complete the 60 scenarios decisions, the computer will provide a random value for the revaluation of the stock index. Once this value is known, the earnings in terms of EU can be calculated for this part of the experiment.

For this example, the following table shows the amount of EU you would obtain if you choose the alternative B for different possible values of the stock index revaluation (these values are only examples and will not necessarily occur when the random value appreciation/depreciation rate will be provided).

Option B

97.000 EU
Equivalent to 97% of the investment:
97% recovery of the investment
+

Stock index revaluation in 3 years.	i) 97% of the initial investment	ii) 10% over the stock index revaluation in 3 years	Final outcome for option B: i) + ii)
120%	97.000 EU	100.000×10%×120% = 12.000 EU	97.000 + 12.000 = **109.000 EU**
60%	97.000 EU	100.000×10%×60% = 6.000 EU	97.000 + 6.000 = **103.000 EU**
20%	97.000 EU	100.000×10%×20% = 2.000 EU	97.000 + 2.000 = **99.000 EU**
10%	97.000 EU	100.000×10%×10% = 1.000 EU	97.000 + 1.000 = **98.000 EU**
0%	97.000 EU	No value*	**97.000 EU**
-10%	97.000 EU	No value*	**97.000 EU**
-20%	97.000 EU	No value*	**97.000 EU**
-60%	97.000 EU	No value*	**97.000 EU**

* No value because the stock index revaluation was not positive

Below there is another example for alternative B, which will appear in one of the 60 scenarios:

Option B

103.000 EU

Equivalent to 103% of the investment:

100% recovery of the investment + 3% interest rate in 3 years (1% annually)

+

In this example, the outcomes for the alternative B would be:

Stock index revaluation in 3 years.	**i)** **103% of the initial investment**	**ii)** **60% of the stock index revaluation in 3 years.**	**Final outcome for option B:** **i) + ii)**
120%	103.000 EU	100.000×60%×120% = 72.000 EU	103.000 + 72.000 = **175.000 EU**
60%	103.000 EU	100.000×60%×60% = 36.000 EU	103.000 + 36.000 = **139.000 EU**
20%	103.000 EU	100.000×60%×20% = 12.000 EU	103.000 +12.000 = **115.000 EU**
10%	103.000 EU	100.000×60%×10% = 6.000 EU	103.000 + 6.000 = **109.000 EU**
0%	103.000 EU	No value*	**103.000 EU**
-10%	103.000 EU	No value *	**103.000 EU**
-20%	103.000 EU	No value *	**103.000 EU**
-60%	103.000 EU	No value *	**103.000 EU**

* No value because the stock market revaluation was not positive

Additional information about alternative B

For a correct interpretation, we now explain the economic meaning of the stock index revaluation:

Stock index revaluation in 3 years.	**How to interpret the average evolution of the assets prices in the stock market.**
120%	The assets price was multiplied by 2,2 in 3 years. (Increased a 120%)
60%	The assets price was multiplied by 1,6 in 3 years. (Increased a 60%)
20%	The assets price was multiplied by 1,2 in 3 years. (Increased a 20%)
10%	The assets price was multiplied by 1,1 in 3 years. (Increased a 10%)
0%	The assets price is the same as 3 years ago.
-10%	The assets price was multiplied by 0,9 in 3 years. (Decreased 10%)
-20%	The assets price was multiplied by 0,8 in 3 years. (Decreased 20%)
-60%	The assets price was multiplied by 0,4 in 3 years. (Decreased 60%)

Stock market investments are risky investments since its future performance is uncertain. Therefore, as it has already been explained, the stock index revaluation after 3 years is not known. However it can be assumed that this performance will follow a normal distribution. This assumption is not far from the reality of these financial markets. Therefore, to determine the random value of the stock index revaluation (needed to calculate the outcome for part ii) of Alternative B) it is assumed that the performance of the index follows a normal distribution. So, we have assumed a volatility (risk) of our stock index of 15.6% each year, which in three years is a risk of 15.6% × 3 = 46.8%. In practical terms it means that we can establish the following probability distribution for the revaluation of our stock index at 3 years:

Stock index revaluation after 3 years:	**Probability**
Less than -100%	0.82%
Less than -80%	2.35%
Less than -60%	6.18%
Less than -40%	13.27%
Less than -20%	24.66%
Less than 0%	40.04%
More than 0%	59.96%
More than 20%	43.47%
More than 40%	27.79%
More than 60%	15.18%
More than 80%	7.17%
More than 100%	2.96%

Actually, we are particularly interested in the above table to see which are the odds for the revaluation to be positive, since only in this case the ii) part of the alternative B offers you gains.

For example, the ninth row of the mentioned table:

More than 60%	15.18%

is interpreted as follows: the chance that the index revaluation in three years was greater than 60% is 15.18%.

2. SECOND PART OF EXPERIMENTAL SESSION

After the investment part of the experiment, some lotteries will be presented to you and you will have to choose again under different situations; chance and your own choices will determine your earnings in the second part of the experiment.

3. THIRD PART OF EXPERIMENTAL SESSION

Finally a questionnaire will be presented to you in order to provide your personal details and some issues related to the experiment. Thank you very much for your participation.